Evaluating employment policies : four essays

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L'évaluation des politiques de l'emploi

Quatre essais

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A la mémoire de mon grand-père, Gérard Guitard

A mes chers parents José et Dominique

A mon frère Benoît

A François et Sébastien

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Résumé

Cette thèse propose dans un premier temps une évaluation structurelle des effets microéconomiques de deux politiques phares du Plan d'Aide au retour à l'Emploi (PARE) implémenté en France en 2001 : l'accompagnement et la formation des demandeurs d'emploi. La création d'entreprise étant souvent citée comme une alternative à ces politiques, on établit dans un second temps un modèle du cycle de vie des travailleurs indépendants. Toutefois, ne disposant du coût social des mesures étudiées, une analyse coût-bénéfice complète n'a pu être réalisée dans le cadre de ce travail. D'un point de vue méthodologique l'approche structurelle est abordée ici comme une extension des évaluations en forme réduite et non comme leur antithèse. Compte tenu des difficultés algorithmiques posées par cette méthode, on accorde une attention particulière aux techniques d'optimisation utilisées et on s'attache - suivant les recommandations de Judd - à simplifier au maximum la mise en oeuvre des estimations grâce à l'usage du logiciel AMPL.

Mots-Clés *: Mobilité professionnelle - Chômage : Modèle de durée et de recherche - Politique publique de l'emploi - Capital humain, choix d'occupation, productivité du travail - Modèles à choix discrets dynamiques - Algorithme d'optimisation - Modèle de durée*

Abstract

Evaluating employment policies : four essays

This thesis provides a structural evaluation of microeconomic effects of two policies of the PARE (Policies package for Return to Employment) put work in France since 2001, counseling and training the unemployed. As entrepreneurship is often seen as an alternative way to escape unemployment, I also build a model of the live cycle of independent workers. Yet, as I do not have access to the social cost of the measure I surveyed, I am not able to carry out a full cost-benefit analysis. From a methodological point of view this structural approach is used as an extension of the reduced-form evaluations and not as their opposite. For the sake of computation tractability one pays a special attention to optimization technics and follows Judd's recommendation who suggests algorithmic simplifications, easy to work out with the software AMPL.

Keywords *: J62 Job, Occupational, and Intergenerational Mobility - J64 Unemployment : Models, Duration, Incidence, and Job Search - J66 Public Policy - J24 Human Capital ; Skills ; Occupational Choice ; Labor Productivity - C35 Discrete Regression and Qualitative Choice Models ; Discrete Regressors - C61 Optimization Techniques ; Programming Models ; Dynamic Analysis - C41 Duration Analysis*

Résumé en français

Cette thèse s'inscrit dans la littérature économique traitant des politiques publiques de l'emploi. Le marché du travail a été le cœur des préoccupations des économistes depuis l'apparition du chômage structurel dans les années 1970 dans les pays de l'OCDE. Des remèdes très différents ont été prescrits depuis lors, avec des résultats apparemment contrastés selon les pays et les modèles de société : il est couramment admis que le chômage a baissé dans les pays du nord et en Grande-Bretagne, tandis qu'il persiste en Europe continentale.

Cette thèse aborde les questions de l'accompagnement des chômeurs (chapitre 2), de leur formation (chapitre 3) et des opportunités que leur offre le travail indépendant et la création d'entreprise (chapitres 4 et 5). Du point de vue de la théorie économique plusieurs imperfections de marché justifient l'intervention publique dans ces domaines :

– L'existence de frictions sur le marché du travail : une solution dans ce cas consiste à proposer des mesures d'accompagnement et d'aide à la recherche d'emploi.
– Une inadéquation entre les compétences et savoirs des travailleurs et la demande des employeurs, justifiant par exemple la mise en place de stages de formation pour les chômeurs.
– Des conditions adverses à la création d'entreprise ou au financement d'un

projet personnel : contraintes de crédit, manque de capital humain spécifique (gestion, savoir-faire entrepreneurial).

Outre ces questions de fond, cette thèse examine aussi différentes méthodologies d'évaluation économique des politiques publiques. Bien que des dizaines de mesures en faveur de l'emploi aient été implémentées depuis 30 ans, l'idée que l'on puisse -et qu'il faille- évaluer l'impact de ces politiques objectivement est relativement neuf dans l'esprit des décideurs.
Le développement et l'acculturation des économistes aux méthodes par variables instrumentales (IV)et aux expérimentations ont permis depuis une quinzaine d'années d'atteindre cet objectif. Cependant d'un point de vue méthodologique plusieurs critiques peuvent être faites à ces méthodes :

- Les estimateurs par variables instrumentales sont écrits sous l'hypothèse qu'il n'y a pas d'effet d'équilibre partiel ou général. Cette hypothèse est crédible si la politique étudiée cible un petit nombre d'individus, mais elle est difficile à maintenir dès que l'on cherche à implémenter une politique de grande ampleur. Cette question est régulièrement soulevée par les praticiens de l'emploi qui sont sensibles aux enseignements des expérimentations sociales en la matière et se posent la question de la généralisation des dispositifs testés.
- Les estimateurs par variables instrumentales ne donnent que des estimateurs locaux, c'est la contrepartie de leur relatif agnostisme. Il est ainsi difficile d'extrapoler les impacts à d'autres populations que l'échantillon étudié. De même ces estimateurs éludent en général l'aspect dynamique des dispostifs testés qui sont pourtant essentiels en pratique.

Le premier point -les effets d'équilibre- est abordé dans les chapitres 2 et 3. En réponse au deuxième point, je développe un modèle structurel au chapitre 5.

Du point de vue de l'étude des politiques publiques les chapitres 2 et 3 constituent une évaluation économique de l'accompagnement et la formation du chômeurs. Toutefois ne disposant pas du coût social des mesures étudiées, une analyse coût-bénéfice complète n'a pu être réalisée dans le cadre de cette thèse. Les chapitres 4 et 5 ne sont pas des évaluations mais plutôt des travaux préliminaires à de futures évaluations des politiques cherchant à favoriser la création d'entreprise comme le dispositif NACRE en France.

L'introduction 1 revient sur la littérature propre aux différents thèmes abordés : l'accompagnement et la formation des chômeurs, le travail indépendant et la création d'entreprise, le modèle à choix discrets dynamiques, le logiciel AMPL. Les sections suivantes décrivent la progression des quatre chapitres qui la composent.

Les effets d'équilibre de l'accompagnement

`Cet article a été co-écrit avec Pierre Cahuc, Bruno Crépon et Marc Gurgand.`

Dans ce chapitre nous avons développé un modèle d'équilibre partiel sur le marché du travail à partir du modèle d'appariement classique de Pissaridès. Nous avons cherché à identifier si l'accompagnement augmente réellement le nombre de contacts chômeurs-employeurs ou s'il ne fait que déplacer les offres d'emplois des chômeurs vers les chômeurs accompagnés au détriment des chômeurs non accompagnés. Nous partons de l'évaluation que Crépon, Dejemeppe et Gurgand (2005) ont faite des prestations offertes aux demandeurs d'emploi dans le cadre du PARE entre 2001 et 2004. Cette évaluation, qui trouvait des effets favorables de l'accompagnement sur la durée de chômage et plus encore sur la récurrence, ne tenait pas compte des effets d'équilibre. Le contexte de cette politique amène pourtant à se poser sérieusement la question de tels effets. D'abord, il peut exister des effets d'éviction importants, les

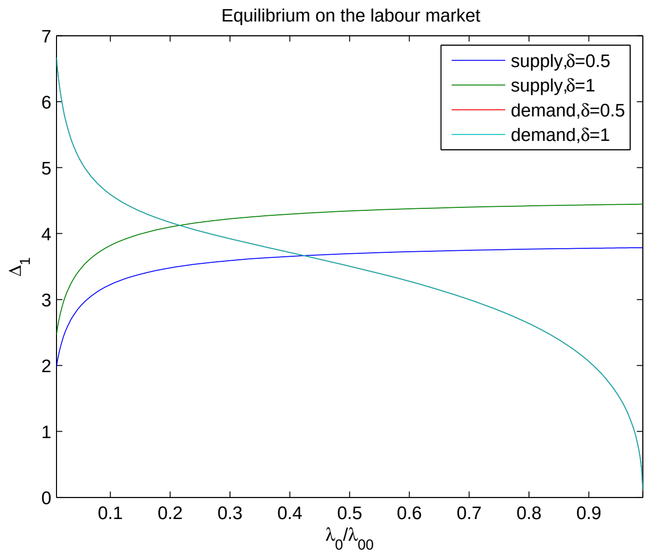

FIG. 1 – Equilibre sur le marché du travail

chômeurs traités étant simplement replacés plus haut dans une file d'attente. Dans ce cas, la politique a simultanément un effet positif sur les traités et négatif sur les non-traités, si bien que la comparaison des traités et des non-traités ne mesure pas l'effet bénéfique qu'il y aurait, à l'équilibre, à renforcer l'accompagnement. Ensuite, la plus grande fluidité du marché résultant de comportements de recherche d'emploi plus efficaces, peut entraîner des créations d'emploi plus nombreuses. Enfin, les demandeurs accompagnés peuvent aussi se montrer plus exigeants, ce qui peut venir limiter l'effet précédent. Au total, les effets d'équilibre sont ambigus, et leur évaluation nécessite de décrire explicitement la formation de l'équilibre et d'estimer les paramètres du modèle, de manière à évaluer empiriquement l'existence, la direction et l'ampleur d'éventuels effets d'équilibre.

Dans ce modèle, l'accompagnement accroît l'utilité de réservation des demandeurs d'emploi et les pousse donc à refuser des offres qu'ils auraient acceptées s'ils n'avaient pas été accompagnés. Ce comportement exerce une externalité sur la création de poste, réduisant le taux d'arrivée des offres pour les chômeurs ne bénéficiant pas de l'accompagnement. Le modèle est estimé sur des données qui échantillonnent des dispositifs d'accompagnement intensif qui sont proposés à près de 12.5% des chômeurs depuis la réforme des politiques d'aide au retour à l'emploi (PARE) en 2001. Nous trouvons des effets significativement favorables du conseil sur les taux de sortie du chômage des demandeurs accompagnés. En revanche nous trouvons aussi que l'accompagnement réduit les taux de sortie du chômage des demandeurs exclus du dispositif. Cet effet est suffisamment grand pour réduire le taux moyen de sortie du chômage pour l'échantillon complet (accompagnés et non accompagnés) et cela même quand la part de chômeurs accompagnés est faible. Ce résultat met en exergue que les évaluations ne reposant que sur des comparaisons entre le groupe de traitement et le groupe de contrôle peut conduire à des conclusions erronées *même quand une petite proportion de la population est traitée.*

Pour évaluer l'ampleur de ces effets, on estime les paramètres du modèle avec les données issues du Fichier historique statistique de l'ANPE utilisées par Crépon, Dejemepe et Gurgand (2005). On estime par le maximum de vraisemblance la structure de toutes les durées observées (durée au chômage non-accompagné, durée au chômage accompagné et durée en emploi) tout en imposant sur les paramètres toutes les contraintes qui sont impliquées par la structure du modèle à l'état stationnaire et notamment les relations qui doivent être vérifiées à l'équilibre : dans cet équilibre, les deux variables endogènes sont le taux d'arrivée des offres, λ_0, qui dépend lui-même directement du nombre d'emplois créés à chaque période par les entreprises, et λ_1 qui découle des décisions optimales des demandeurs d'emploi. Les paramètres qui déterminent le niveau de cet équilibre sont l'intensité du traitement, l'efficacité structurelle de ce traitement, le coût fixe de création de poste et la rentabilité des emplois, l'efficacité du matching, ainsi que le taux d'intérêt.

Nous découpons l'échantillon en 1562 cellules. Une cellule comprend tous les in-

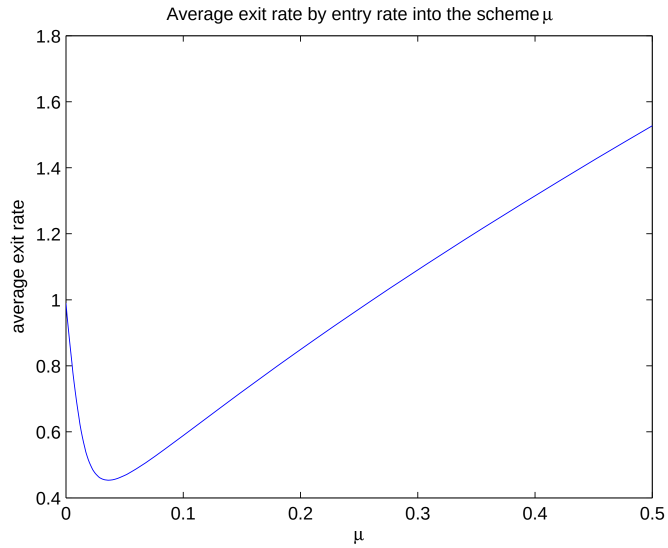

FIG. 2 – Impact du conseil sur le taux de sortie des non-traités

dividus partageant les mêmes caractéristiques observées : âge, sexe, région et niveau d'étude. A un niveau plus fin, un micromarché contient tous les individus d'une cellule partageant également les mêmes caractéristiques inobservées. Dans notre cas, nous spécifions que les individus se répartissent en deux types inobservés : une cellule contient donc 2 micromarchés. Cette façon de faire est cohérente avec l'hypothèse qu'une multitude de sous-marchés coexistent au sein du marché du travail et permet d'estimer le maximum de vraisemblance de façon parcimonieuse et efficace par le logiciel d'optimisation non linéaire sous contraintes KNITRO AMPL. Pour chaque cellule on obtient deux ensembles de paramètres (un pour chaque type inobservé). Il faut environ 5 jours pour mener à bien l'ensemble des 1562 estimations. Les échecs de convergence sont rares (moins de 5 cellules). Nous pouvons ensuite analyser les paramètres obtenus sur l'ensemble des micromarchés de façon non paramétrique ou imposer une structure linéaire en fonction des caractéristiques observées.

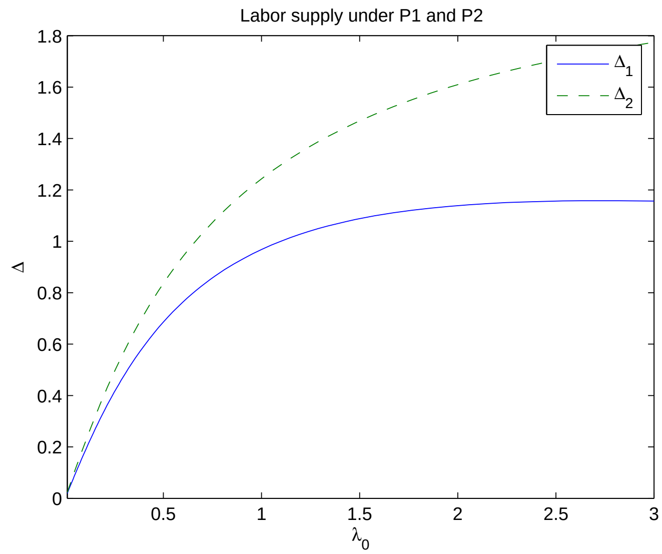

FIG. 3 – Offre de travail

Les effets d'équilibre de la formation

`Cet article a été coécrit avec Marc Ferracci.`

Ce chapitre transpose à la formation la démarche du chapitre 3. Il s'agit aussi d'un modèle d'équilibre partiel du marché du travail construit à partir du modèle d'appariement de Pissaridès et la méthode d'estimation est similaire.

Les effets d'équilibre passent pas trois canaux principaux : d'abord, les formés évincent les non formés car ils sont en compétition pour les mêmes emplois alors que les premiers sont davantage employables que les seconds. Le deuxième effet est une baisse du taux d'arrivée des offres dû à une plus grande exigence des traités (formés ou en formation) qui refusent les offres d'emploi trop courtes. Ce comportement pousse les employeurs à créer moins d'offres car la probabilité de refus de ces offres par les chômeurs augmente. Enfin, en allongeant le temps moyen en emploi, la formation fait baisser les coûts de vacance et incite ainsi les employeurs a créer

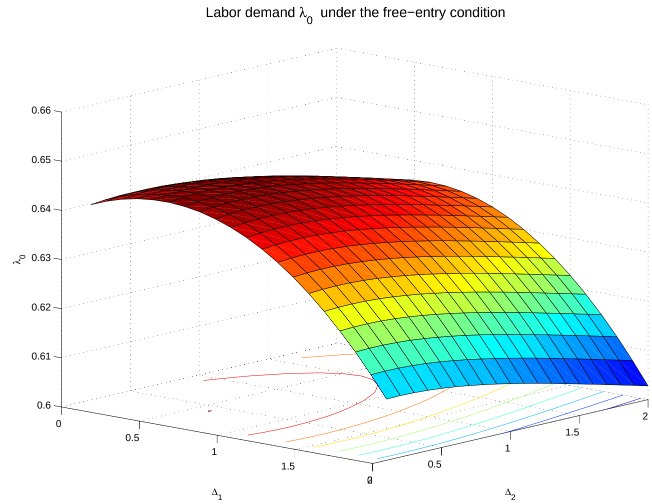

FIG. 4 – Demande de travail

plus de postes. Les deux premiers effets sont négatifs. Le troisième effet est un effet de demande et constitue à l'inverse des deux autres une externalité positive pour les non traités. L'effet total sera donc ambigu et nécessite comme au chapitre 2 un modèle explicite.

Nous travaillons à partir du FHS. Nous effectuons un découpage sensiblement différent du chapitre précédent.

ANPE - *Agence National Pour l'Emploi*
Service publique de l'emploi, depuis le 1er janvier 2009 'Pole Emploi'.
Etablissement public.

ASSEDIC - *Association pour l'Emploi dans l'Industrie et le Commerce*
Agences locales de l'UNEDIC.

BMO - *enquête Besoin de Main d'Œuvre*
Enquête annule conduite par les ASSEDIC depuis 2001.
Recolte les prévisions d'ouverture de poste dans les entreprises pour l'année en cours
Aide l'ANPE dans sa définition des programmes de formation.

FNA - *Fichier National des ASSEDIC*
Enregistre les chômeurs au niveau national.

FTSJ - *French Training System for Job seekers*

PARE - *Plan d'Aide au Retour à l'Emploi*
Réforme introduite en septembre 2001.
Renforcement de l'accompagnement des demandeurs d'emploi par l'ANPE.
Entretien individuel obligatoire avec un conseiller de l'ANPE tous les 6 mois.

UNEDIC - *Union Nationale interprofessionnelle pour l'Emploi Dans l'Industrie et le Commerce*
Institution en charge du versement de l'assurance chômage.
Gérée par les partenaires sociaux.
Depuis 2001 propose et achète des offres de formation

	μ	ε	λ_0	$\lambda_0\bar{F}(\Delta_1)$	$\lambda_0\bar{G}(\Delta_2)$	λ_{00} (simulated)	ψ_f/ψ_g	Δ_1	Δ_2
Mean	0.253	3.125	2.517	1.516	1.836	1.930	1.406	0.31	0.32

TAB. 1 – Espérance des paramètres estimés (μ le taux d'entrée dans la formation,ε le taux de sortie de la formation, λ_0 le taux de sortie du chômage des non traité,$\lambda_0\bar{F}(\Delta_1)$ le taux de sortie du chômage des personnes en formation, $\lambda_0\bar{G}(\Delta_2)$ le taux de sortie du chômage des chômeurs formés et λ_{00} le taux de sortie du chômage en l'absence de politique)

	μ	ε	λ_0	$\lambda_0\bar{F}(\Delta_1)$	$\lambda_0\bar{G}(\Delta_2)$	λ_{00}	ψ_f	ψ_g	Δ_1	Δ_2
C10	0.003	0.391	0.177	0.053	0.175	0.000	0.049	0.060	0.001	0.001
C25	0.030	3.877	0.377	0.306	0.345	0.009	0.207	0.214	0.004	0.002
C50	0.104	18.752	1.017	0.700	0.760	0.490	1.613	1.049	0.013	0.010
C75	0.877	204.549	12.322	6.769	8.310	6.135	7.489	4.601	0.120	0.147
C90	2.830	822.480	53.077	37.815	45.265	15.608	23.838	15.009	0.500	1.129

TAB. 2 – Centile des paramètres estimés

La stratégie d'identification et d'estimation est en revanche extrêmement proche. La souplesse d'écriture qu'offre AMPL permet de faire la transposition d'un problème à l'autre très simplement. Les temps de calculs sont du même ordre (5 jours environ).

Nous trouvons que contrairement au chapitre 2 les effets de éviction sont moins importants que les effets de demande : les effets d'équilibre sont importants mais positifs.

Quels chômeurs deviennent des travailleurs indépendants dans le GSOEP

Ce chapitre décrit dans les grandes lignes le parcours des travailleurs indépendants du German Socio-Economic Panel (GSOEP). J'y présente le contexte institutionnel et tente d'y dresser un portrait stylisé des créateurs d'entreprise en Alle-

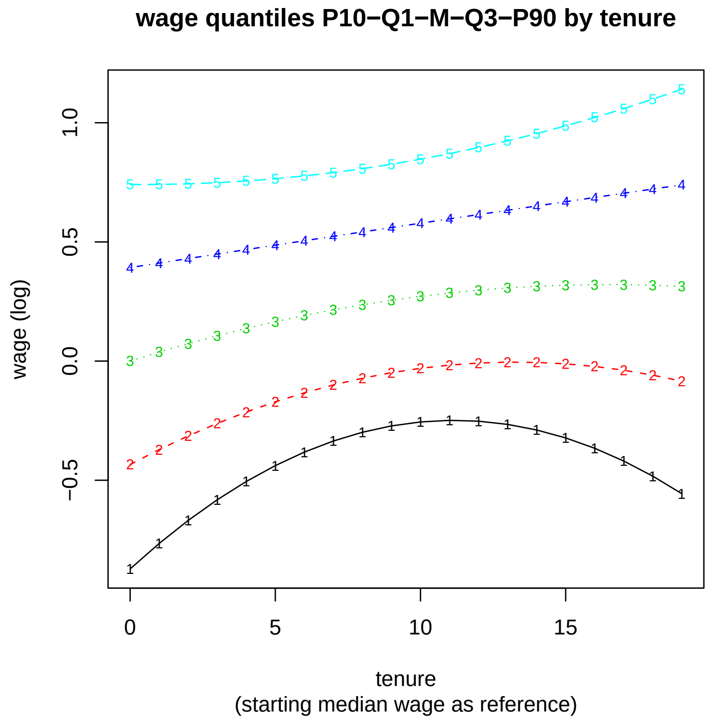

FIG. 5 – Centiles des revenus du travail P10-Q1-M-Q3-P90 par ancienneté dans l'emploi

magne.

C'est un préalable au chapitre 5, à ce titre les techniques économétriques restent simples : statistiques descriptives, estimateurs logit simple. L'idée n'est en aucun cas de mettre au point une nouvelle stratégie instrumentale ou structurelle, mais bien de calibrer des valeurs typiques des paramètres de la création et la survie de leur activité. Le GSOEP est un panel de ménages vivant en Allemagne. Il enquête chaque année près de 20.000 personnes depuis 1984. Il sert notamment à alimenter le Panel Européen. A un instant donné, près de 5% des personnes interrogées travaillent en tant qu'indépendants. Sur plus de 20 ans 12% des personnes ont été un jour ou l'autre travailleur indépendant. A partir de ces données je montre que l'on observe un nombre important d'entrées ou de sorties vers l'entrepreneuriat. Les estimations

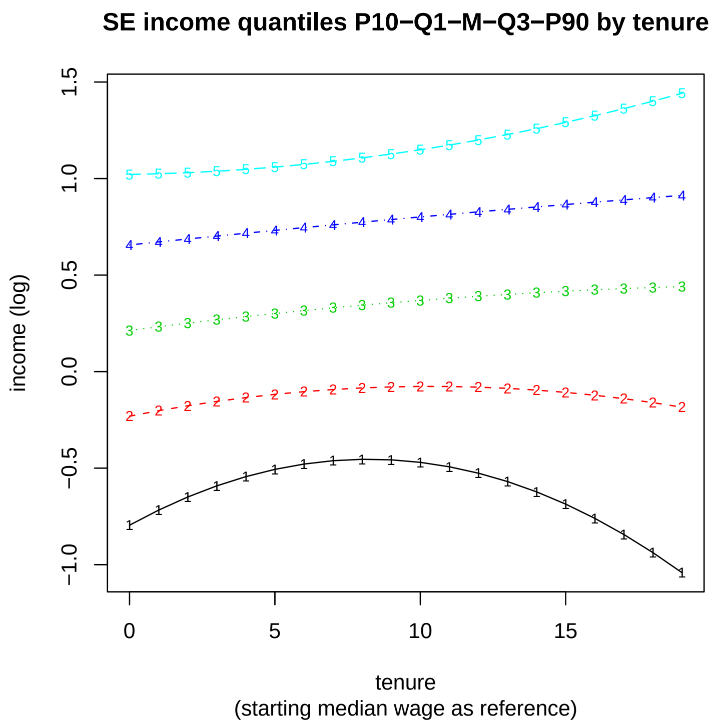

FIG. 6 – Centiles des revenus du travail indépendant P10-Q1-M-Q3-P90 par ancienneté de l'entreprise

en forme réduite semblent mettre en évidence une prédominance du capital humain comme catalyseur de la création d'entreprise, en particulier via l'expérience familiale en la matière. Comprendre le motif économique de ces transitions justifie l'écriture d'un modèle structurel.

Dans le détail

- on donne des stats. desc. des indépendants du GSOEP.
- A partir d'une variable de statut professionel s_{it} on met en place :
  - Un modèle calendaire des transitions du salariat/chômage/indépendance vers l'indépendance.
  - Un modèle à hasard proportionnel sur les épisodes d'indépendance.
- On discute de l'exogénéité (education,fortune), de la censure à gauche des variables d'accumulation (expérience), de la robustesse (comparant l'approche calendaire et Cox).

Un modèle structurel du cycle de vie des indépendants

Dans ce chapitre je construis un modèle structurel du cycle de vie des travailleurs indépendants en Allemagne. A partir des faits stylisés rassemblés au chapitre précédent, j'établis un modèle à choix discrets dynamiques, où les travailleurs choisissent année après années leur type d'activité (emploi salarié, indépendance, chômage) en fonction de leurs coûts, de leurs revenus espérés et des opportunités qui s'offrent à eux (offre d'emploi, possibilité d'emprunter pour financer une création d'entreprise). Au delà des questions économiques que j'ai eu l'occasion de soulever au chapitre précédent, je cherche ici à montrer que l'on peut simplifier considérablement l'estimation d'un modèle structurel complexe grâce à la méthodologie "en une étape" de Judd and Su (2006). J'estime une version **simplifiée** des équations de Bellman qui en

	(a)	(b)	(c)	(d)	(e)	(f)
Statut du père	0.006	0.004	0.004	0.005	0.004	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Nationalité allemande	0.005	0.004	0.004	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education professionalisante	0.003	(0.002)	(0.002)	(0.002)	(0.002)	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
'Meister'					0.008	0.006
					(0.004)	(0.004)
Education supérieure	0.014	0.014	0.013	0.01	0.01	0.009
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Ancienneté	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
A déjà été entrepreneur		0.003	0.003	0.002	0.002	0.002
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
A déjà été chômeur		0.002	0.001	0.001	0.001	0.001
		(0.001)	(0.001)	(<.001)	(<.001)	(<.001)
Age	0	0	0	0	0	0
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Age au début de l'enquête			0	0	0	0
			(<.001)	(<.001)	(<.001)	(<.001)
Business Cycle						-0.005
						(0.017)
P.obs	0.011	0.011	0.011	0.011	0.011	0.011
N. obs	56887	56887	56887	45707	45707	29065

Tab. 3 – Taux de transition annuel de l'emploi vers l'indépendance

	(a)	(b)	(c)	(d)	(e)	(f)
Statut du	0.023	0.024	0.022	0.019	0.019	0.018
père	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.016)
Nationalité	0.009	0.009	0.008	0.008	0.008	0.006
allemande	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)
Education	0.01	0.009	0.008	0.007	0.007	0.007
professionalisante	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
'Meister'					0.019	0.009
					(0.022)	(0.019)
Education	0.126	0.115	0.107	0.128	0.128	0.144
supérieure.	(0.038)	(0.036)	(0.031)	(0.044)	(0.044)	(0.054)
Ancienneté	0.001	0.001	0.001	0	0	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
A déjà été		0.001	0.001	0.002	0.002	0.001
entrepreneur		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
A déjà été		-0.004	-0.005	0	0	-0.003
chômeur		(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Age	-0.001	-0.001	0	0	0	0
	(<.001)	(<.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age au			-0.001	-0.001	-0.001	-0.001
début de l'enquête			(0.001)	(0.001)	(0.001)	(0.001)
Business						0.051
Cycle						(0.081)
P.obs	0.023	0.023	0.023	0.024	0.024	0.027
N. obs	5942	5942	5942	4013	4013	2819

TAB. 4 – Taux de transition annuel du chômage vers l'indépendance

	(a)	(b)	(c)	(d)	(e)	(f)
Statut du	0.028	0.029	0.028	0.027	0.027	0.005
père	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.019)
Nationalité	0.034	0.038	0.037	0.036	0.036	0.019
allemande	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)	(0.026)
Education	0.007	0.006	0.007	0.007	0.006	0.013
professionalisante	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.01)
'Meister'					0.017	0.031
					(0.029)	(0.03)
Education	0.037	0.036	0.039	0.051	0.051	0.078
supérieure.	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)
Ancienneté	0.014	0.013	0.015	0.016	0.016	0.016
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A déjà été		-0.014	-0.011	-0.01	-0.01	-0.008
entrepreneur		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
A déja été		-0.009	-0.005	0.002	0.002	0.001
chômeur		(0.008)	(0.009)	(0.003)	(0.003)	(0.004)
Age	0	0	-0.003	-0.003	-0.003	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Age au			0.002	0.003	0.003	0
début de l'enquête			(0.002)	(0.002)	(0.002)	(0.002)
Business						-0.138
Cycle						(0.207)
P.obs	0.845	0.845	0.845	0.848	0.848	0.844
N. obs	6490	6490	6490	5423	5423	3833

TAB. 5 – Taux de survie annuel dans l'indépendance

	α^U	α^W	α^S
Père	1.4	-0.103	0.05
indépendant	0.217	0.102	0.003
Experience	-0.224	-0.121	-0.131
comme salarié	0.041	0.332	0.014
Experience	0.192	0.074	0.081
comme indépendant	<0.001	0.04	0.032
Ancienneté	-	0.164	0.013
		0.746	0.04
Capital	-0.183	0.025	-0.028
financier	0.702	0.291	0.338
Tendance	-0.140	0.012	-0.036
temporelle	0.684	0.069	0.006
Constante	6.567	7.141	8.7754
(Type 1)	0.822	0.015	0.607
Constante	10.425	10.253	10.7118
	1.416	0.851	0.069
σ	1.773	0.640	0.560
N.OBS	531	531	531

TAB. 6 – La structure des revenus par occupation, U=chômage, W=salariat, S=indépendance (les ecart-types sont sous les estimateurs)

découlent.

Conclusion

Les politiques publiques de l'emploi ont engendré une littérature volumineuse ces dernières années. Face à cet enjeu majeur qu'est la réduction du chômage dans nos économies, elle commence seulement à éclairer le débat public, grâce notamment à la diffusion des expériences contrôlées. Mais à peine ces méthodes commencent-elles à être connues du public que deux critiques ou questions se font entendre notamment de la part des praticiens :

c^U	c^W	c^S
0	≈ 3	≈ 5

TAB. 7 – Coût du loisir par occupation

$p_{Type=1}$	$p_{Type=2}$
0.039	0.961

TAB. 8 – Les types inobservés (2 types)

	ρ_W^U	ρ_W^W	ρ_W^S	ρ_S^U	ρ_S^W	ρ_S^S
Père indépendant	-0,2	-0,75	-0,3	-0,1	-0,100	0,8
Experience comme salarié	0,100	-0,700	0,000	0	0,200	-0,1
Expérience comme indépendant	1,000	-1,400	0,200	0	0,200	-0,6
Ancienneté	-	-0,2	0,1	-	-0,400	-0,2
Capital financier	-0,100	0,500	0,000	-0,2	0,500	-0,100
Tendance temporelle	OUI	OUI	OUI	OUI	OUI	OUI
Constante (Type 1)	-2	2	-0,2	-2	-2,000	2
Constante (Type 2)	-4	2.3	0,2	-2,1	0	2,2
N.OBS	531	531	531	531	531	531

TAB. 9 – Les probabilités de transition par occupation

- Si les politiques testées ont des effets d'équilibre, les généraliser à un groupe plus large que l'échantillon expérimental risque d'entraîner des effets inattendus, que seule l'écriture d'un modèle explicite permet de scénariser les trajectoires professionnelles.
- Un modèle totalement agnostique permet-il de prévoir l'effet à moyen terme des politiques expérimentée ? Comment extrapoler les conclusions à d'autres groupes que l'échantillon test ?

Dans cette thèse je me suis proposé d'examiner les conséquences de deux de ces limites sur l'évaluation des deux politiques du PARE en France, l'accompagnement et la formation des demandeurs d'emploi et sur un sujet général cher à l'opinion, le travail indépendant. J'ai adopté une stratégie structurelle dans les chapitres 2,3 et 5. Cette approche structurelle a été abordée comme une extension des évaluations en forme réduite et non comme leur antithèse. Conscient des difficultés d'implémentation, je me suis attaché suivant les recommandations de Judd à simplifier à maximum la mise en oeuvre grâce à l'usage du logiciel AMPL.
D'une façon générale beaucoup de travail reste à faire pour affiner et rendre robustes ces résulats. Les conclusions économiques faites dans chacun des chapitres 2,3 et 5 sont donc à prendre avec prudence et devront être étayées par des recherches futures.

Le chapitre 1 Ce chapitre apporte quelques faits nouveaux.

Tout d'abord, la non prise en compte des effets d'équilibre peuvent induire en erreur le chercheur dans son évaluation de la politique **même quand le groupe de traitement est petit.** Par exemple ici, une évaluation naïve en différences de différences sur le taux de sortie du chômage pousse à conclure que l'accompagnement des demandeurs augmente le taux de sortie moyen (traités et non traités) alors que la conclusion peut être inversée quand l'on tient compte des effets d'équilibre même quand la proportion des traités est faible.
Ensuite, les effets d'équilibre peuvent être non monotones. Dans le cas de l'accom-

pagnement : l'externalité négative sur le taux de sortie moyen du chômage va en s'amplifiant avant d'atteindre un maximum -lorsque le chômage est devenu très dual- puis diminue jusqu'au point où tout le monde est traité instantanément : le chômage est redevenu uniforme.

Troisièmement on voit que ces effets d'équilibre varient beaucoup selon les micro-marchés. Ils sont notamment plus importants pour les travailleurs les plus en marge de l'emploi comme les femmes et les moins qualifiés.

Ces résultats ont aussi des conséquences en terme de politiques publiques. Ils montrent tout d'abord qu'il est important de bien tenir compte des effets d'équilibre dans les évaluations. Leur impact n'est pas sans nuance : la non-monotonicité de ces effets pour l'accompagnement par exemple rend crédible l'hypothèse selon laquelle il est bénéfique si on l'applique à grande échelle et contre-productive si on se contente de l'appliquer à petite ou moyenne échelle.

Il reste bien sûr beaucoup de questions pour de futures recherches. Le résultat montre une grande hétérogénéité des effets. L'origine de cette hétérogénéité est encore mal comprise. Le contexte institutionnel est aussi très important comme le rapportent de nombreux praticiens des métiers de l'accompagnement. D'un point de vue méthodologique les questions d'identification, de stabilité des algorithmes et de robustesse des estimateurs mériteraient d'être approfondies.

Le chapitre 2 Ce chapitre met en évidence des effets d'équilibre de la formation. Il montre que sur les données de Fichier Historique de l'ANPE, l'effet demande excède les effets d'éviction. La formation augmente le temps moyen d'employabilité des chômeurs faisant ainsi baisser les coûts de vacance : les employeurs sont incités à créer des postes supplémentaires **accessibles à tous -formés ou non-**. Cet effet est apparemment supérieur à l'effet attendu de file d'attente ou d'éviction dans lequel ce sont les chômeurs formés qui bénéficient de cette amélioration aux dépens

des chômeurs non formés ou en formation.
Le modèle explique aussi le fort effet lock-in observé pour les chômeurs en formation. Pour eux, quitter la formation signifie renoncer à un allongement moyen des contrats. Une offre reçue en cours de formation doit donc être particulièrement avantageuse -c'est à dire longue dans ce modèle- pour pouvoir les débaucher.
Comme au chapitre précédent les effets d'équilibre sont aussi importants pour l'évaluateur des politiques publiques. Ils modifient sensiblement l'effet direct de la formation à savoir l'allongement moyen des contrats notamment en faisant apparaître une durée de réservation pour les chômeurs formés ou en formation et en modifiant le taux d'arrivée des offres. Ne pas en tenir compte c'est surestimer l'impact de la formation sur les durées en emploi et sous-estimer son effet sur les taux d'arrivée des offres.

Comme au chapitre 2 il reste beaucoup de questions pour de futures recherches : identification, stabilité et robustesse comme je l'ai mentionné plus haut mais aussi sur les effets de stocks (taux de chômage et d'emploi).

Le chapitre 3 Ce chapitre montre que la formation initiale a un impact sur la création d'entreprise que l'on soit employé ou chômeur même si le contexte familial reste au moins aussi prédominant. L'apprentissage mène sans surprise à fonder des entreprises dans l'artisanat et l'industrie tandis qu'une formation supérieure (technique ou non) conduit vers des activités tertiaires.
On montre aussi que les chômeurs tentent plus souvent de créer leur entreprise que les employés -toutes choses égales par ailleurs-, ce qui est cohérent avec l'idée que l'indépendance peut être une échappatoire à une imperfection du marché du travail. L'effet de l'éducation semble plus fort pour les activités tertiaires que les activités indépendantes du secteur secondaire.
Concernant la survie des activités des indépendants seule l'ancienneté semble avoir

un pouvoir explicatif.

Si l'on interprète ces constatations au pied de la lettre, on sera donc enclin à financer les filières professionnelles supérieures pour favoriser la création d'entreprise.

Ces résultats semblent assez robustes à la spécification mais n'ont en revanche **aucune portée causale ou structurelle**. Le but du chapitre suivant est précisément de les rendre compatibles avec un modèle économique explicite. Hors du cadre de cette thèse une expérimentation sociale serait aussi très intéressante pour mettre à jour des relations causales.

Le chapitre 4 On retrouve une partie des résultats sur la hiérarchie et la structure des revenus par type d'occupation. Ce chapitre est cependant encore très incomplet. L'échantillon du chapitre 4 a été considérablement réduit pour des raisons de faisabilité technique. L'identification simultanée des équations d'opportunité -les fonctions ρ- et de choix -les fonctions valeurs- est encore difficile à ce stade : les résultats que j'obtiens sont peut-être entièrement dus à mes choix de paramétrisation. Un boostrap de plus grande ampleur doit encore être réalisé. A partir de là la cohérence avec les estimateurs du chapitre précédent est à vérifier. D'une manière générale, comme aux chapitres 2 et 3, il reste beaucoup de questions pour de futures recherches : identification du modèle, stabilité de l'algorithme de résolution et robustesse des estimateurs.

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Chapitre 1

Introduction

Cette thèse s'inscrit dans la littérature économique traitant des politiques publiques de l'emploi. Le marché du travail a été le cœur des préoccupations des économistes depuis l'apparition du chômage structurel dans les années 1970 dans les pays de l'OCDE. Des remèdes très différents ont été prescrits depuis lors, avec des résultats apparemment contrastés selon les pays et les modèles de société : il est couramment admis que le chômage a baissé dans les pays du nord et en Grande-Bretagne, tandis qu'il persiste en Europe continentale.

Cette thèse aborde les questions de l'accompagnement des chômeurs (chapitre 2), de leur formation (chapitre 3) et des opportunités que leur offre le travail indépendant et la création d'entreprise (chapitres 4 et 5). Du point de vue de la théorie économique plusieurs imperfections de marché justifient l'intervention publique dans ces domaines :

– L'existence de frictions sur le marché du travail : une solution dans ce cas consiste à proposer des mesures d'accompagnement et d'aide à la recherche d'emploi.
– Une inadéquation entre les compétences et savoirs des travailleurs et la de-

mande des employeurs, justifiant par exemple la mise en place de stages de formation pour les chômeurs.
- Des conditions adverses à la création d'entreprise ou au financement d'un projet personnel : contraintes de crédit, manque de capital humain spécifique (gestion, savoir-faire entrepreneurial).

Outre ces questions de fond, cette thèse examine aussi différentes méthodologies d'évaluation économique des politiques publiques. Bien que des dizaines de mesures en faveur de l'emploi aient été implémentées depuis 30 ans, l'idée que l'on puisse -et qu'il faille- évaluer l'impact de ces politiques objectivement est relativement neuf dans l'esprit des décideurs.
Le développement et l'acculturation des économistes aux méthodes par variables instrumentales (IV)et aux expérimentations ont permis depuis une quinzaine d'années d'atteindre cet objectif. Cependant d'un point de vue méthodologique plusieurs critiques peuvent être faites à ces méthodes :

- Les estimateurs par variables instrumentales sont écrits sous l'hypothèse qu'il n'y a pas d'effet d'équilibre partiel ou général. Cette hypothèse est crédible si la politique étudiée cible un petit nombre d'individus, mais elle est difficile à maintenir dès que l'on cherche à implémenter une politique de grande ampleur. Cette question est régulièrement soulevée par les praticiens de l'emploi qui sont sensibles aux enseignements des expérimentations sociales en la matière et se posent la question de la généralisation des dispositifs testés.
- Les estimateurs par variables instrumentales ne donnent que des estimateurs locaux, c'est la contrepartie de leur relatif agnostisme. Il est ainsi difficile d'extrapoler les impacts à d'autres populations que l'échantillon étudié. De même ces estimateurs éludent en général l'aspect dynamique des dispostifs testés qui sont pourtant essentiels en pratique.

Le premier point -les effets d'équilibre- est abordé dans les chapitres 2 et 3. En réponse au deuxième point -la localité et l'agnostisme, je développe un modèle structurel au chapitre 5.

Du point de vue de l'étude des politiques publiques les chapitres 2 et 3 constituent une évaluation économique de l'accompagnement et la formation du chômeurs. Toutefois ne disposant du coût social des mesures étudiées, une analyse coût-bénéfice complète n'a pu être réalisée dans le cadre de cette thèse. Les chapitres 4 et 5 ne sont pas des évaluations et doivent plutôt être considérés comme des travaux préliminaires à de futures évaluations des politiques cherchant à favoriser la création d'entreprise comme le dispositif NACRE en France.

La prochaine section est dédiée à un tour d'horizon de la littérature sur les différents sujets abordés par cette thèse. Les sections suivantes décrivent la progression des quatre chapitres qui la composent.

1.1 Un aperçu de la littérature

Avant de présenter les quatre chapitres de cette thèse, voici une présentation rapide de la littérature relative aux différentes thématiques économiques ou méthodologiques que je vais soulever par la suite.

1.1.1 L'accompagnement et la formation des chômeurs en France

Le système français de l'emploi est assez complexe dans la mesure où il implique trois acteurs : l'État, les régions administratives et les partenaires sociaux. Pour la suite une distinction fondamentale doit être faite entre les chômeurs indemnisables c'est à dire ayant droit à l'assurance chômage et les autres. L'État gère l'Agence nationale pour l'emploi (ANPE) dont le but est de conseiller le demandeur d'emploi, qu'il soit indemnisable ou non. Par ailleurs l'État finance les programmes de formation des chômeurs de longue durée ayant épuisé leurs droits comme les chômeurs non indemnisables touchant les minima sociaux. Les partenaires sociaux gèrent quant à eux l'assurance chômage. Ils sont constitués en association l'Union nationale interprofessionnelle pour l'emploi dans l'industrie et le commerce (UNEDIC). L'UNEDIC intervient au niveau régional via les associations pour l'emploi dans l'industrie et le commerce (ASSEDIC).

En 2001 a vu le jour le Plan d'Aide au Retour à l'Emploi. Cette réforme a modifié en profondeur la relation des demandeurs avec l'ANPE et l'Unédic. Il a été notamment décidé d'organiser un suivi régulier et individualisé pour chaque chômeur, sous la forme d'un entretien bi-annuel (au minimum). Le premier de ces entretiens (idéalement réalisé au moment de l'inscription du chômeur à l'ANPE) est obligatoire et doit permettre au demandeur d'emploi et au conseiller de l'ANPE de s'entendre sur le niveau d'assistance requis pour sa recherche d'emploi. Deux grands types de suivi sont ainsi proposés : le bilan de compétence -pouvant déboucher sur une demande de formation- et l'aide à la recherche d'emploi appelée par la suite accompagnement . Le demandeur est toujours libre d'accepter ou refuser le service qu'on lui propose. En théorie un refus peut aboutir à une réduction des indemnités pour les chômeurs indemnisables. En pratique toutefois ces sanctions sont rares.

En théorie la formation augmentent la productivité des chômeurs et donc leur employabilité (Becker (1964)). Toutefois d'un point de vue empirique les effets de la formation semblent hétérogènes et variables selon le point de la trajectoire où l'on se positionne (inscription au chômage, en cours de chômage, après avoir repris un emploi). Le sujet a donc fait l'objet d'une littérature abondante. Un excellent résumé en a été fait par Crépon, Ferracci and Fougère (2007b). Ils rappellent les quatre principaux effets mis à jour jusqu'ici :

– L'effet de menace (perte immédiate d'utilité pour le chômeur). Au regard de la littérature cet effet semble dominer les gains de productivité future.

– L'effet de lock-in (le temps de la formation, un chômeur ne peut pas chercher d'emploi). Cet effet explique en grande partie le faible impact global de la formation sur le taux de transition du chômage vers l'emploi que mettent en exergue les auteurs.
– L'hétérogénité : l'effet de la formation diffère selon le sexe, la qualification, l'âge des bénéficiaires et leur trajectoire passée sur le marché du travail.
– L'effet sur la durée de l'emploi retrouvé. Il apparaît généralement positif dans les diverses études.

L'accompagnement a fait l'objet d'une littérature plus limitée, à ma connaissance. Je citerai par exemple Davidson and Woodbury (1993), Calmfors (1994) et plus récemment Lise, Seitz and Smith (2005) et Crepon, Dejemeppe and Gurgand (2005). Dans tous les cas, l'accompagnement se distingue nettement de la formation dans la mesure où il vise à améliorer les techniques de recherche d'emploi et non les connaissance ou les savoir-faire professionnels intrinsèques des chômeurs. Crepon, Dejemeppe and Gurgand (2005) mettent ainsi en évidence une diminution relative de la durée au chômage pour les personnes accompagnées ainsi q'une légère augmentation de la durée des emplois retrouvés par ces personnes.

1.1.2 Le travail indépendant et la création d'entreprise

La question du travail indépendant est souvent perçue comme cruciale dans le débat public et suscite les passions : en soutenant à la fois l'innovation et l'emploi, les indépendants sont au cœur de nos économies. Dans la suite de cette thèse, j'entends par indépendant toute personne qui déclare être son propre employeur et de fait cotise directement pour sa sécurité sociale. Cette définition correspond bien au cas allemand que j'étudie dans les deux derniers chapitres et elle est facilement accessible dans les données d'enquête que j'utilise. Il est évident qu'elle recouvre de nombreuses situations économiques (artisanat, industrie, free-lance) et juridiques (entreprise unipersonnelle, société à responsabilité limitée). Je m'intéresserai aux indépendants en tant que travailleurs et j'ignorerai le statut exact de la structure qui les encadre. Je me rattache en ce sens à l'économie du travail et non à l'économie de l'entreprise.

Des articles classiques de macroéconomie tel Romer (1990) Aghion and Howitt (1992) ont mis en exergue le rôle des créateurs d'entreprises comme moteurs de l'innovation et de la croissance. Dans la suite, je m'intéresserai plutôt aux aspects microéconomiques de l'entrepreneuriat. En effet, l'idée de promouvoir le travail indépendant par une série d'incitations microéconomiques et des réformes institutionnelles du marché de travail semble être en vogue chez les politiques ces dernières années. Dans cette thèse j'ai voulu aborder la question du travail indépendant en trois sous-questions :

- La création d'entreprise proprement dite.
- La question de la création d'entreprise par les chômeurs. Dans ce cas, l'indépendance est vue comme un remède aux imperfections sur le marché du travail salarié.
- La survie de l'activité indépendante créée.

En pratique les interventions en faveur de la création d'entreprise recouvrent un large spectre de mesure : compléter une information imparfaite sur les opportunités existantes, corriger les imperfections de marché en supprimant ou desserrant les barrières légales et administratives et les contraintes de crédit, et enfin promouvoir certaines filières menant de façon privilégiée vers une activité indépendante (artisanat, commerce, fournisseur de services free-lance). Avant de conseiller et d'évaluer ces politiques l' économiste appliqué doit comprendre la dynamique du cycle de vie d'un indépendant. Afin de réduire l'impact des contraintes de crédits qui pèsent lourdement sur les transferts de revenus inter-temporels, l'Allemagne a lancé dès 1994 une série de mesures facilitant l'obtention de prêts par les candidats à la création d'entreprise. Le résultat a souvent été considéré comme décevant (Pfeiffer et Reize, 2000) mesuré à l'aune des créations d'emplois durables : le dispositif sélectionne des individus qui auraient souhaité entreprendre de toute façon (*always takers*) sans pour autant les aider à créer une activité durable. D'un autre coté, la formation est peut-être un meilleur levier pour développer la fibre et les compétences entrepreneuriales : dans ce cas améliorer l'éducation entrepreneuriale constitue peut-être le sésame des futures politiques en faveur du travail indépendant. Dans le contexte allemand, où l'éducation professionnelle a été la clef d'une bonne intégration des jeunes sur le marché du travail depuis des décennies, la question des interactions entre emploi salarié, chômage et travail indépendant est particulièrement intéressante. Au delà de la simple comparaison entre les effets des différents type de capitaux humains (contexte familial, education, experience professionnelle), il s'agit aussi d'évaluer si les politiques en faveur de l'éducation entrepreneuriale peuvent effectivement accélérer la mobilité sociale.

Jusque récemment, la littérature a privilégié la question de la création d'entreprise et a relativement laissé de coté la question de la pérennité de ces entreprises. Evan et Jovanovic (1989) construisent un modèle statique de choix d'occupation sous contraintes de crédit. Ils estiment ensuite ce modèle sur des données du National Longitudinal Survey et mettent en évidence un impact positif des actifs détenus sur la probabilité d'entreprendre sur la période 1976-1978 ayant contrôlé pour les effets d'éducation et du contexte familial. Toutefois le montant d'actifs détenus par un ménage a de grande chance d'être endogène : si l'accès au crédit est imparfait, les personnes désireuses d'entreprendre auront tendance à sur-épargner. Pour corriger de cet effet Blanchflower (1998) utilise les dons et les héritages reçus disponibles dans l'enquête National Child Development Study 1981 : ils confirment cependant un impact positif du capital financier sur la probabilité d'entreprendre. Il apparaît aussi qu'un enfant d'entrepreneur ou qu'un ancien apprenti ont beaucoup plus de chance de devenir entrepreneur au cours de leur cursus. En revanche les auteurs ne parviennent pas à montrer un impact de facteurs psychologiques comme l'aversion au risque. La question de l'impact des contraintes de crédit sur la création d'entreprise a encore été étudiée par Hurst et Lusardi (2004) qui -en utilisant les héritages et les plus-values immobilières engrangées par les ménages- montrent que l'effet du capital financier sur la probabilité d'entreprendre est très convexe sur la période 1989-1994. Pour une expérimentation contrôlée on peut signaler : Banerjee et Duflo (2002).

Même si les chômeurs qui tentent de créer leur entreprise diffèrent par leurs caractéristiques socio-démographiques des indépendants en général, peu d'articles leurs sont consacrés. Evans et Leighton (1989) exploitent les données du National Survey of Young Men et fait apparaître que les travailleurs à bas salaires, les chômeurs et les travailleurs intérimaires ont plus de chance que les titulaires d'un emploi stable et bien rémunéré de devenir indépendants. Toutefois il n'est pas clair par exemple si l'entrepreneuriat constitue une réelle opportunité de carrière ou est juste une façon de déguiser une période d'inactivité pour éviter la stigmatisation qui l'accompagne.

Malgré son importance, peu de choses ont été faites sur la carrière des individus après qu'ils se soient lancés dans une activité indépendante. Cet intérêt sélectif pour la création d'entreprise au détriment de ce qui se passe ensuite est peut-être le résultat de l'idée commune que les économistes doivent essentiellement se focaliser sur l'efficacité des marchés : dans ce cadre de pensée la seule raison qui justifie une intervention extérieure en matière d'entrepreneuriat est un accès imparfait au crédit qui empêcherait les bons potentiels de se lancer dans une activité indépendante. En revanche une fois cette barrière levée, la survie de l'entreprise devrait être laissée aux seules forces du marché : les meilleurs projets survivront, les autres seront condamnés à disparaître. Mon avis est que ce biais résulte aussi de la nature des données dont les économistes appliqués disposent. Enregistrer une activité indépendante dans une enquête ménage est une chose assez difficile, la suivre au cours du temps peut s'avérer franchement ardu. En d'autres termes, la faible part de la littérature consacrée à la survie des activité indépendantes est peut-être dû au caractère hybride de ce champ d'étude, à mi-chemin entre l'économie du travail et l'économie de l'entreprise. Signalons que Hamilton (2000) utilise une alternative au PSID -l'enquête Income and Program Participation- et met en évidence que de nombreuses personnes deviennent indépendantes et le restent en dépit de revenus moindres que ceux offerts à leurs homologues salariés. Taylor (1999) se concentre sur l'espérance de vie des activités indépendantes enregistrées dans le panel British Household Panel Survey et il s'avère que près de 40% des entreprises nouvellement créées ne survivent pas à leur première année. Dans ce contexte, les anciens salariés sont relativement avantagés vis-à-vis des ex-chômeurs.

1.1.3 Evaluation et effets d'équilibres

La plupart des évaluations de politiques publiques reposent sur la comparaison des participants à la politique et des non-participants. Mais les différences entre le groupe de traitement et de contrôle ne mesurent effectivement l'impact de la politique en question, uniquement si le groupe de contrôle n'est pas affecté par la dite politique : c'est le principe de 'non interference' (Rubin, 1978) ou d' 'unité stable' (Angrist, Imbens and Rubin, 1996). Or, en pratique, il se peut que la politique en question ait un impact sur le groupe de contrôle. Par exemple, Heckman, Lochner and Taber (1998) illustrent ce point dans le domaine scolaire. Cette question, qui est abordée dans une revue de littérature par Meghir (2006), est particulièrement pertinente dans le cas des politiques d'offre de travail (par exemple modifiant les incitations des chômeurs ou leur suivi par le service public de l'emploi). A l'origine ces politiques d'offre visent à augmenter le nombre d'emplois occupés dans l'économie. Assez rapidement cette augmentation de l'offre interagit avec la demande de travail, ce qui induit par définition une modification de l'équilibre sur le marché du travail. Ensuite, ces politiques peuvent induire des effets de files d'attentes : dans ce cas les personnes traitées évincent les non traités de l'emploi, car ils compétitent sur les mêmes postes alors que la politique favorise les premiers sans aider les seconds .

Bien que connus de long date, ces questions ont bénéficié d 'un intérêt empirique assez limité à ce jour. Davidson and Woodbury (1993) et Calmfors (1994) sont deux contributions historiques. Plus récemment, Lise, Seitz and Smith (2005) calibrent un modèle d'équilibre du marché du travail et trouve que le programme d'incitations du Self-Sufficient Project au Canada a beaucoup moins d'impact à l'équilibre que ce que les études se fondant sur la comparaison directe entre groupe de contrôle et groupe de traitement avaient mis en évidence. Toujours à partir d'un modèle calibré, Albrecht, van den Berg and Vroman (2005) trouvent qu'un programme de formation en Suède a eu des effets d'équilibre significatifs. A l'inverse, Blundell, Costa Dias, Meghir and Van Reenen (2004) trouvent que les effets directs et les effets d'équilibre sont similaires dans le cas du New Deal for Young People en Grande-Bretagne. Ils utilisent des méthodes d'appariement pour parvenir à ce résultat. Enfin, à partir d'un modèle théorique, Van der Linden (2005) montre que les évaluations microéconomiques et évaluations d'équilibre risquent d'aboutir à des conclusions différentes quand les salaires et les efforts de recherche sont endogènes.

1.1.4 Les modèles à choix discrets dynamiques

A l'opposé des expérimentations sociales qui veulent le plus souvent apparaître comme agnostiques -c'est à dire interprétables sans l'appui littéral d'un modèle théorique- ou en tous cas dont les données ne sont pas engendrées directement par un modèle théorique, les modèles à choix discrets dynamiques sont des extensions des modèles microéconomiques de comportements qui doivent être capables d'engendrer des trajectoires observées. Suivant Eckstein and Wolpin (1989) la littérature relative aux modèles à choix discrets dynamique a quatre grandes caractéristiques :

- Le problème d'optimisation est forward-looking
- Le nombre de choix dont dispose l'agent est fini (la séquence des choix est discrète et couvre à chaque étape un nombre fini de possibilités)
- On identifie des paramètres structurels c'est à dire provenant de fonctions objectives (goûts, capacités, contraintes)
- La structure de l'erreur est partie intégrante du modèle, en ce sens l'économétrie et le modèle théorique sont indissociables.

Ce champ repose sur le calcul de fonction valeurs associées à chacun des choix par récurrence arrière ou autres techniques de programmation dynamique (Bellman 1957). On peut citer deux papiers classiques, Rust (1987) qui propose un modèle de remplacement optimal des véhicules d'une flotte de bus et Keane and Wolpin (1997) qui écrivent et estiment un modèle de choix d'éducation et de choix d'occupations pour les jeunes adultes du NLSY.
Toutefois ces modèles sont souvent perçus comme difficiles voir inextricables dont l'aspect calculatoires peut s'avérer complexe :

- L'identification économétrique est difficile.
- L'estimation demande de maximiser une vraisemblance très complexe dans laquelle vient s'imbriquer les résolutions d'équations Bellman.
- La résolution d'équation de Bellman est souvent coûteuse en temps et en mémoire et de fait impraticable au dessus d'une certaine dimension (souvent assez petite <10). C'est la malédiction de la dimension.

Rust (1994) a proposé d'introduire une part d'aléas dans les algorithmes pour briser cette malédiction de la dimension. Judd (2006) propose une méthode en une étape pour éviter la résolution imbriquée et résoudre en une étape le maximum de vraisemblance et les équations de Bellman. Cette remarque est au coeur des chapitres 2 et 3 et 5 (cf. section 1.1.5).

1.1.5 Le logiciel AMPL

Estimer des modèles d'équilibre ou de choix discrets dynamiques revient à faire de l'écono métrie dite structurelle. Traditionnellement l'économètre procède alors en deux étapes :

- Écrire une routine de résolution du problème théorique (équilibre de marché, choix d'occupation) pour chaque valeur des paramètres d'intérêt.
- Appeler cette routine dans la vraisemblance associée aux données à chaque étape de la maximisation de celle-ci.

Cette méthode est souvent qualifiée de méthode 'nestée'. Très intuitive elle comporte cependant deux défauts majeurs :

- Elle est coûteuse en temps de calcul : à chaque itération du maximum de vraisemblance on calcule un équilibre, son gradient et parfois sa hessienne, même pour des points éloignés de la vraie valeur de l'estimateur.
- Une modification -même mineure- du modèle théorique sous-jacent est coûteuse en temps de re-progammation : en effet il faut réécrire une routine d'équilibre et s'assurer qu'elle reste cohérente avec la routine qui optimise la vraisemblance

Or Judd and Su (2006), estiment un de ces problèmes en une étape, en optimisant la vraisemblance sous contraintes des équations structurelles (équilibre ou comportement) :

- Le calcul va plus vite, on fait les deux choses à la fois.

- Le problème s'écrit de façon standard grâce des logiciels "front-end" comme AMPL ou TOMLAB. La modification du modèle se fait très facilement. Il n'y a plus de dérivée à calculer et de connexion entre les deux routines à vérifier
- Le front-end est indépendant du solver en lui même : on écrit le pseudo-code sous AMPL par exemple qui le transforme code C ou C++ directement utilisable par de nombreux solvers disponibles sur le marché. L'optimisation non linéaire sous-contraintes a fait l'objet de développements constants depuis 20 ou 30 ans dans la communauté des ingénieurs et des mathématiciens appliqués. On peut donc bénéficier à très faible coup du meilleur solver existant sans avoir besoin de réinventer la roue avec les solvers par défaut de MATLAB ou Gauss ou d'apprendre un langage spécifique à ce solver.

Cette méthode a bien sûr ses inconvénients. Je citerai les deux qui m'ont paru les plus contraignants. D'abord l'effet "boîte noire" des algorithmes de AMPL. On sait assez peu de choses sur les méthodes utilisées et la logique les itérations effectuées. Si les résulats sont raisonnables on passera sur cet aspect, mais en cas de non-convergence ou de convergence douteuse, il est difficile de remonter aux origines du problème. L'autre défaut majeur est que la plupart des solvers associés à AMPL ne fournissent pas la hessienne et le gradient qu'ils utilisent et qui sont pourtant indispensables au calcul de la variance des solutions par δ-méthode. Il faut donc calculer cette variance dans une seconde étape par bootstrap ou par δ-méthode en utilisant un logiciel classique comme MATLAB.

1.2 The equilibrium effects of counseling

`Cet article a été co-écrit avec Pierre Cahuc, Bruno Crépon et Marc Gurgand.`

Dans ce chapitre nous avons développé un modèle d'équilibre partiel sur le marché du travail à partir du modèle d'appariement classique de Pissaridès. Nous avons cherché à identifier si l'accompagnement augmente réellement le nombre de contacts chômeurs-employeurs ou s'il ne fait que déplacer les offres d'emplois des chômeurs vers les chômeurs accompagnés au détriment des chômeurs non accompagnés. Nous partons de l'évaluation que Crépon, Dejemeppe et Gurgand (2005) ont faite des prestations offertes aux demandeurs d'emploi dans le cadre du PARE entre 2001 et 2004. Cette évaluation, qui trouvait des effets favorables de l'accompagnement sur la durée de chômage et plus encore sur la récurrence, ne tenait pas compte des effets d'équilibre. Le contexte de cette politique amène pourtant à se poser sérieusement la question de tels effets. D'abord, il peut exister des effets d'éviction importants, les chômeurs traités étant simplement replacés plus haut dans une file d'attente. Dans ce cas, la politique a simultanément un effet positif sur les traités et négatif sur les non-traités, si bien que la comparaison des traités et des non-traités ne mesure pas l'effet bénéfique qu'il y aurait, à l'équilibre, à renforcer l'accompagnement. Ensuite, la plus grande fluidité du marché résultant de comportements de recherche d'emploi plus efficaces, peut entraîner des créations d'emploi plus nombreuses. Enfin, les demandeurs accompagnés peuvent aussi se montrer plus exigeants, ce qui peut venir limiter l'effet précédent. Au total, les effets d'équilibre sont ambigus, et leur évaluation nécessite de décrire explicitement la formation de l'équilibre et d'estimer les paramètres du modèle, de manière à évaluer empiriquement l'existence, la direction et l'ampleur d'éventuels effets d'équilibre.

Dans ce modèle, l'accompagnement accroît l'utilité de réservation des demandeurs d'emploi et les pousse donc à refuser des offres qu'ils auraient acceptées s'ils n'avaient pas été accompagnés. Ce comportement exerce une externalité sur la création de poste, réduisant le taux d'arrivée des offres pour les chômeurs ne bénéficiant pas de l'accompagnement. Le modèle est estimé sur des données qui échantillonnent des dispositifs d'accompagnement intensif qui sont proposés à près de 12.5% des chômeurs depuis la réforme des politiques d'aide au retour à l'emploi (PARE) en 2001. Nous trouvons des effets significativement favorables du conseil sur les taux de sortie du chômage des demandeurs accompagnés. En revanche nous trouvons aussi que l'accompagnement réduit les taux de sortie du chômage des demandeurs exclus du dispositif. Cet effet est suffisamment grand pour réduire le taux moyen de sortie du chômage pour l'échantillon complet (accompagnés et non accompagnés) et cela même quand la part de chômeurs accompagnés est faible. Ce résultat met en exergue que les évaluations ne reposant que sur des comparaisons entre le groupe de traitement et le groupe de contrôle peut conduire à des conclusions erronées *même quand une petite proportion de la population est traitée.*

Pour évaluer l'ampleur de ces effets, on estime les paramètres du modèle avec les données issues du Fichier historique statistique de l'ANPE utilisées par Crépon, Dejemepe et Gurgand (2005). On estime par le maximum de vraisemblance la structure de toutes les durées observées (durée au chômage non-accompagné, durée au chômage accompagné et durée en emploi) tout en imposant sur les paramètres toutes les contraintes qui sont impliquées par la structure du modèle à l'état stationnaire et notamment les relations qui doivent être vérifiées à l'équilibre : dans cet équilibre, les deux variables endogènes sont le taux d'arrivée des offres, λ_0, qui dépend lui-même directement du nombre d'emplois créés à chaque période par les entreprises, et λ_1 qui découle des décisions optimales des demandeurs d'emploi. Les paramètres qui déterminent le niveau de cet équilibre sont l'intensité du traitement, l'efficacité structurelle de ce traitement, le coût fixe de création de poste et la rentabilité des emplois, l'efficacité du matching, ainsi que le taux d'intérêt.

Nous découpons l'échantillon en 1562 cellules. Une cellule comprend tous les individus partageant les mêmes caractéristiques observées : âge, sexe, région et niveau d'étude. A un niveau plus fin, un micromarché contient tous les individus d'une cellule partageant également les mêmes caractéristiques inobservées. Dans notre cas, nous spécifions que les individus se répartissent en deux types inobservés : une cellule contient donc 2 micromarchés. Cette façon de faire est cohérente avec l'hypothèse qu'une multitude de sous-marchés coexistent au sein du marché du travail et permet d'estimer le maximum de vraisemblance de façon parcimonieuse et efficace par le logiciel d'optimisation non linéaire sous contraintes KNITRO AMPL. Pour chaque cellule on obtient deux ensembles de paramètres (un pour chaque type inobservé). Il faut environ 5 jours pour mener à bien l'ensemble des 1562 estimations. Les échecs de convergence sont rares (moins de 5 cellules). Nous pouvons ensuite analyser les paramètres obtenus sur l'ensemble des micromarchés de façon non paramétrique ou imposer une structure linéaire en fonction des caractéristiques observées.

1.3 The equilibrium effects of training

`Cet article a été coécrit avec Marc Ferracci.`

Ce chapitre transpose à la formation la démarche du chapitre 3. Il s'agit aussi d'un modèle d'équilibre partiel du marché du travail construit à partir du modèle d'appariement de Pissaridès et la méthode d'estimation est similaire.

Les effets d'équilibre passent pas trois canaux principaux : d'abord, les formés évincent les non formés car ils sont en compétition pour les mêmes emplois alors que les premiers sont davantage employables que les seconds. Le deuxième effet est une baisse du taux d'arrivée des offres dû à une plus grande exigence des traités (formés ou en formation) qui refusent les offres d'emploi trop courtes. Ce comportement pousse les employeurs à créer moins d'offres car la probabilité de refus de ces offres par les chômeurs augmente. Enfin, en allongeant le temps moyen en emploi, la formation fait baisser les coûts de vacance et incite ainsi les employeurs a créer plus de postes. Les deux premiers effets sont négatifs. Le troisième effet est un effet de demande et constitue à l'inverse des deux autres une externalité positive pour les non traités. L'effet total sera donc ambigu et nécessite comme au chapitre 2 un modèle explicite.

Nous travaillons à partir du FHS. Nous effectuons un découpage sensiblement différent du chapitre précédent. La stratégie d'identification et d'estimation est en revanche extrêmement proche. La souplesse d'écriture qu'offre AMPL permet de faire la transposition d'un problème à l'autre très simplement. Les temps de calculs sont du même ordre (5 jours environ).
Nous trouvons que contrairement au chapitre 2 les effets d'éviction sont moins importants que les effets de demande : les effets d'équilibre sont importants mais positifs.

1.4 Who goes from unemployment to self-employment ? Evidence from the German Socio-Economic Panel

Ce chapitre décrit dans les grandes lignes le parcours des travailleurs indépendants du German Socio-Economic Panel (GSOEP). J'y présente le contexte institutionnel et tente d'y dresser un portrait stylisé des créateurs d'entreprise en Allemagne. C'est un préalable au chapitre 5, à ce titre les techniques économétriques restent simples : statistiques descriptives, estimateurs logit simple. L'idée n'est en aucun cas de mettre au point une nouvelle stratégie Instrumentale ou structurelle, mais bien de calibrer des valeurs typiques des paramètres de la création et la survie de leur activité. Le GSOEP est un panel de ménage vivant en Allemagne. Il enquête chaque année près de 20.000 personnes depuis 1984. Il sert notamment à alimenter le Panel Européen. A un instant donné, près de 5% des personnes interrogés travaillent en tant qu'indépendants. Sur plus 20 ans 12% des personnes ont été un jour ou l'autre travailleur indépendant. A partir de ces données je montre que l'on observe un nombre important d'entrées ou de sorties vers l'entrepreneuriat. Les estimations en forme réduite semblent mettre en évidence une prédominance du capital humain comme catalyseur de la création d'entreprise, en particulier via l'expérience familiale en la matière. Comprendre le motif économique de ces transitions justifie l'écriture d'un modèle structurel.

1.5 A Dynamic, Structural, Empirical Model of Entrepreneurship

Dans ce chapitre je construis un modèle structurel du cycle de vie des travailleurs indépendants en Allemagne. A partir des faits stylisés rassemblés au chapitre précédent, j'établis un modèle à choix discrets dynamiques, où les travailleurs choisissent année après années leur type d'activité (emploi salarié, indépendance, chômage) en fonction de leurs coûts, de leurs revenus espérés et des opportunités qui s'offrent à eux (offre d'emploi, possibilité d'emprunter pour financer une création d'entreprise). Au delà des questions économiques que j'ai eu l'occasion de soulever au chapitre précédent, je cherche ici à montrer que l'on peut simplifier considérablement l'estimation d'un modèle structurel complexe grâce à la méthodologie "en une étape" de Judd and Su (2006). J'estime une version **simplifiée** des équations de Bellman qui en découlent.

Chapitre 2

The equilibrium effects of counseling

`This chapter is an extract an article written with Pierre Cahuc, Bruno Crépon and Marc Gurgand.`

2.1 Introduction

Most policy evaluations are based on comparing the behavior of participants and non participants in the policy. But the differences in outcome between the treatment group and the control group do estimate the policy mean impact only if the outcomes of the control group are not influenced by the policy, the so-called 'no-interference' (Rubin, 1978) or 'stable unit treatment value' (Angrist, Imbens and Rubin, 1996) assumption. However, the policy may have equilibrium effects that affect the untreated altogether. For instance, Heckman, Lochner and Taber (1998) strikingly illustrate this point in the context of education policies. This issue, which is discussed in a broader perspective in the survey of Meghir (2006), is particularly relevant to the evaluation of labor supply based policies (such as increasing incentives or monitoring the unemployed). First, they generally aim at increasing the overall number of filled jobs, which depends on the interactions between aggregate labor supply and labor demand. Second, these policies may induce displacement effects : treated persons may crowd out the untreated because they compete for the same jobs.

Although they have been long recognized, these questions have received limited empirical attention to date. Davidson and Woodbury (1993) and Calmfors (1994) are early contributions. More recently, Lise, Seitz and Smith (2005) using a calibrated equilibrium model of the labor market find that the Self-Sufficient Project incentive program in Canada has much less impact in equilibrium than implied by direct comparison of treated and untreated. Also using a calibrated model, Albrecht, van den Berg and Vroman (2005) find equilibrium effects of a Swedish training program to be stronger than implied by direct comparison. In contrast, based on a comparison of pilot with control areas, Blundell, Costa Dias, Meghir and Van Reenen (2004) find that direct and equilibrium evaluations of the New Deal for Young People in the U.K. provide similar results. Looking at theoretical models of counseling, Van der Linden (2005) shows that micro and equilibrium evaluations are likely to differ widely when job search effort and wages are endogenous.

The aim of this paper is to evaluate the effects of the intensive counseling schemes that are provided to about 12.5 percent of the unemployed workers in France since the 2001 unemployment policy reform (PARE[1]). Estimating differences in outcomes between the treatment group and the control group, Crepon, Dejemeppe and Gurgand (2005) find significant favorable effects of the counseling schemes on both unemployment and employment spells. However, their results do not account for equilibrium effects, since it is assumed that the outcomes of the control group are not influenced by the counseling schemes. Our paper looks further into their contribution by accounting for such effects in a simple equilibrium model of the labor market with search and matching, inspired from Pissarides (2000).

[1]PARE is the acronym of Plan d'Aide au Retour à l'Emploi.

In order to account for the prevalence of the minimum wage among low skilled workers in France, we develop a model with a single exogenous wage but where jobs differ in their duration. In this framework, counseling affects non-counseled unemployed workers through three channels. First, the counseled have a higher rate of entry into jobs so that, holding job creation, they displace the non-counseled. Second, by increasing search efficiency, counseling induces employers to create more jobs since they expect to recruit workers more quickly. Third, counseling also reduces the overall job offers because counseled unemployed workers, who are more choosy than those who do not benefit from counseling, refuse more job offers. This behavior induces employers to open less job vacancies since the probability to meet a worker who refuses a job offer is larger when there is counseling. In our model, the sum of these effects implies that treatment reduces the *untreated* exit rate from unemployment in equilibrium. Accordingly, even if simple comparison finds higher exit rate out of unemployment for counseled workers, whether counseling really increases the *treated* exit rate in equilibrium and what is the overall effect of the policy remains an empirical matter.

Using administrative data on 1/12th of individual unemployment spells in France between 2001 and 2004, we estimate a structural model over unemployment duration, subsequent employment duration (if any) and duration until treatment, imposing all the structure implied by equilibrium conditions. This identifies all parameters, except for the matching function elasticity that has to be calibrated. Based on this, we can estimate the full effect of the policy, in the observed equilibrium, for both treated and untreated, and we find that it is less positive than based on direct comparison of both groups.

We can also simulate the impact of expanding counseling. When doing so, we find that the causal relation between the share of counseled workers and the average exit rate from unemployment in the population is J-shaped. Counseling reduces the average exit rate from unemployment when a small share of unemployed workers are counseled. When the share of counseled workers is large enough, spreading counseling raises the average exit rate from unemployment. One source of this striking result is a composition effect : the share of untreated, who are adversely affected by the policy, decreases when the policy expands. But another mechanisms plays an important role. Counseling creates an opportunity cost of accepting job offers because counseled job seekers who find jobs can loose them and will then have to wait a while before benefiting from counseling again. This opportunity cost is higher when the probability to be counseled again, after the accepted job is lost, is lower. Therefore, counseled workers are very choosy and then refuse many job offers when the probability of counseling (or equivalently the share of workers who benefit from counseling) is low. This mechanism implies that increases in the share of counseled workers raise the share of very choosy workers when there are few counseled workers. Thus, expanding counseling when only a small share of workers are counseled discourages job creation and exerts a negative impact on the average exit rate out of unemployment. When the probability of receiving counseling increases, treated workers are much less choosy, the negative impact is smaller and the composition effect dominates. This result shows that a naive evaluation, relying on a simple comparison of the outcomes of participants and non participants that neglects equilibrium effects can lead to the wrong conclusion that counseling increases the average exit rate of unemployment, especially when the share of counseled unemployed is small. However, generalizing counseling to all job seekers is, in this model, desirable.

Please note that we only focus on the microeconomic effects of the measure for the unemployed and we do not aim at assessing the social cost for the public employment service[2].

[2] On the top of the methodological reason that motivates this choice, one must note the complexity of the counseling sector, mixing public and private stakeholders, with a great diversity of contractual obligations.

The paper is organized as follows : the labor market model is presented in section 2. Section 3 presents the econometric strategy and section 4 describes the data. Results are given in section 5 and section 6 concludes.

2.2 The model

We consider a labor market with a continuum of infinitely-lived risk neutral workers whose measure is normalized to one. Their common discount rate r, is strictly positive. Time is continuous. Workers can be in three different states : (1) employed, (2) unemployed and counseled, (3) unemployed and not counseled. Upon entering unemployment, workers are not counseled. They then enter into counseled status at a rate μ and they keep on receiving counseling until they find a job. Since we focus on low skilled workers, we only consider workers who are paid the minimum wage, which is treated as an exogenous variable. The duration of jobs, denoted by Δ, is match specific. It depends on the adaptability of the worker for the type of job to which he is matched. When a worker and a job are matched, the duration of the job is drawn in an exogenous distribution whose cumulative distribution function is denoted by F, which is assumed to be continously differentiable over its entire support. The distribution of durations of job offers is the same for counseled and non counseled unemployed workers. However, since it will be shown that counseled and non counseled unemployed workers do not have the same reservation utilities, the distributions of durations of jobs that are *accepted* by counseled and non counseled unemployed are different.

The assumption that there is a binding minimum wage and heterogeneous job durations allows us to account for two important features of the French labor market for low skilled workers. First, in France, the legal minimum wage covers about 15 percent of the workforce and most low skilled workers are covered by the minimum wage. Moreover, more than 70 percent of workers are recruited with fixed term contracts, this figure being higher for low skilled workers. This feature is related to the specificity of the French labor market regulation with very high firing costs (mainly due to costly legal procedures) for regular contracts with no fixed duration that induce employers to offer fixed term contracts. Therefore, the heterogeneity of low skilled jobs relies much more on differences in contract durations rather than on wage differences.

There is an endogenous number of jobs. Each job can be either vacant of filled. Filled jobs produce y units of the numeraire good per unit of time, whereas vacant jobs cost h per unit of time.

Vacant jobs and unemployed workers (the only job seekers, by assumption) are brought together in pairs through an imperfect matching process. This process is represented by the customary matching function, which relates total contacts per unit of time to the seekers on each side of the market. Let us denote by u_0 and u_1 the number of non counseled and counseled unemployed workers respectively. In our set-up, the only potential effect of counseling is to increase the arrival rate of job offers to the counseled unemployed workers. Let us normalize to one the number of efficiency units of job search per unit of time of each non counseled unemployed worker. Counseled unemployed workers are assumed to produce a different number of efficiency units of search, denoted by $\delta \geq 1$. In this setting, the number of efficiency units of job search per unit of time amounts to $s = u_0 + \delta u_1$.

If v denotes the number of job vacancies, the number of employer-worker contacts per unit of time is given by $M(s, v)$, where the matching function M is twice continuously differentiable, increasing and concave in both of its arguments, and linearly homogeneous. Linear homogeneity of the matching function allows us to express the probability per unit of time for a vacant job (unemployed worker) to meet an unemployed worker (a vacant job) as a function of the labor market tightness ratio, $\theta = v/s$. A vacant job can meet on average $M(s, v)/v = m(\theta)$ unemployed workers per unit of time, with $m'(\cdot) < 0$. Similarly, the rate at which counseled and non counseled unemployed job seekers can meet jobs is $\lambda_1 = \delta\theta m(\theta)$ and $\lambda_0 = \theta m(\theta)$ respectively. It is worth noting that all job contacts do no necessarily lead to job creation because some job matches may yield jobs with duration that can be considered as too short by the worker.

2.2.1 The supply side

Let us denote by V_0, V_1 and $V_e(\Delta)$ the value function of a non counseled unemployed worker, of a counseled unemployed workers and of a worker recruited on a job with duration Δ respectively.

Unemployed workers get unemployment benefits denoted by b. Non counseled unemployed workers become counseled at rate μ and get job offers at rate λ_0. Accordingly, the value function of a non counseled unemployed worker satisfies

$$rV_0 = b + \mu (V_1 - V_0) + \lambda_0 \left(\int_0^{+\infty} \max [V_e(\Delta), V_0] \,\mathrm{d}F(\Delta) - V_0 \right). \tag{2.1}$$

Counseled unemployed workers get job offers at rate $\delta\lambda_0$. Their value function, V_1, satisfies

$$rV_1 = b + \delta\lambda_0 \left(\int_0^{+\infty} \max [V_e(\Delta), V_1] \,\mathrm{d}F(\Delta) - V_1 \right). \tag{2.2}$$

A job seeker who accepts a job offer with duration Δ is paid the wage w for the duration of the job. At the end of the employment spell, the worker will be unemployed and non counseled. Accordingly, the value of a job offer with duration Δ reads

$$V_e(\Delta) = \int_0^{\Delta} we^{-rt}\mathrm{d}t + e^{-r\Delta}V_0.$$

This expression can also be written as follows :

$$V_e(\Delta) = V_0 + \gamma(\Delta)(w - rV_0), \tag{2.3}$$

where $\gamma(\Delta) = \int_0^\Delta e^{-rt}\mathrm{d}t = \left(1 - e^{-\Delta r}\right)/r \geq 0$, is an increasing function of Δ which satisfies $\gamma(0) = 0$. Equation (2.3) implies that $V_e(0) = V_0$ and that workers accept jobs only if $w \geq rV_0$. We assume that this condition is fulfilled. Thus $V_e(\Delta)$ is increasing with respect to Δ. Accordingly, the best rule for non counseled workers is to accept any job whatever its duration $\Delta \geq 0$. We deduce from this that the value function of non counseled unemployed workers, defined in equation (2.1), satisfies

$$rV_0 = b + \mu\left(V_1 - V_0\right) + \lambda_0\left(w - rV_0\right)\int_0^{+\infty}\gamma(\Delta)\mathrm{d}F(\Delta). \tag{2.4}$$

The behavior of counseled job seekers can be different from the behavior of non counseled workers because their expected discounted utility, V_1, is higher than that of non counseled workers if $\delta > 1$. Counseled workers only accept jobs whose duration is above a reservation value, denoted by Δ_1, which is defined by $V_e(\Delta_1) = V_1$. Since V_1 is higher than V_0 and $V_e(\Delta)$ is a strictly increasing function of Δ, with $V_e(0) = V_0$, one gets $\Delta_1 > 0$ if $\delta > 1$. Thus, equation (2.2) can be re-written as follows :

$$rV_1 = b + \delta\lambda_0\int_{\Delta_1}^{+\infty}\left[V_e(\Delta) - V_1\right]\mathrm{d}F(\Delta). \tag{2.5}$$

Moreover, using equation (2.3), the equality $V_e(\Delta_1) = V_1$ reads

$$\gamma(\Delta_1) = \frac{V_1 - V_0}{w - rV_0}. \tag{2.6}$$

It is possible to get, from equations (2.2), (2.4) and (**??**) a relation between λ_0, the arrival rate of job offers to the non counseled unemployed workers, and Δ_1, the reservation duration of counseled unemployed workers, which reads[3] :

$$\frac{(r+\mu)}{\lambda_0}=\delta\int_{\Delta_1}^{+\infty}\frac{\gamma(\Delta)-\gamma(\Delta_1)}{\gamma(\Delta_1)}\mathrm{d}F\left(\Delta\right)-\int_0^{+\infty}\frac{\gamma(\Delta)}{\gamma(\Delta_1)}\mathrm{d}F\left(\Delta\right) \tag{2.7}$$

This equation can be interpreted as a labor supply condition, which defines the relation between the minimum duration of jobs accepted by the counseled job seekers and the arrival rate of job offers. It turns out that the reservation duration of counseled workers increases with the arrival rate of job offers because job seekers become more choosy when they can get more job offers.

2.2.2 The demand side

The demand side describes the behavior of firms. It is assumed that each new match can produce $y > w$ units of good per unit of time for a period Δ. The employer offers a contract that stipulates the duration of the job, Δ, at wage w. At the end of the spell Δ, employers get rid of the worker. The value of a job with duration Δ, denoted by $\Pi(\Delta)$, satisfies

$$\Pi(\Delta)=\int_0^{\Delta}(y-w)e^{-rt}\mathrm{d}t+e^{-\Delta r}\Pi_v, \tag{2.8}$$

where Π_v stands for the value of a vacant job. A vacant job costs h per unit of time and meets a worker at rate $m(\theta)$. The probability to meet an unemployed worker

[3]Equations (2.4) and (2.5) imply :

$$(r{+}\mu)\left(V_1-V_0\right)=\delta\lambda_0\left(w-rV_0\right)\int_{\Delta_1}^{+\infty}\left[\gamma(\Delta)-\left(V_1-V_0\right)\right]\mathrm{d}F\left(\Delta\right){-}\lambda_0\left(w-rV_0\right)\int_0^{+\infty}\gamma(\Delta)\mathrm{d}F\left(\Delta\right),$$

that is

$$r+\mu=\delta\lambda_0\frac{w-rV_0}{V_1-V_0}\int_{\Delta_1}^{+\infty}\gamma(\Delta)dF\left(\Delta\right)-\delta\lambda_0\bar{F}\left(\Delta_1\right)-\lambda_0\frac{w-rV_0}{V_1-V_0}\int_0^{+\infty}\gamma(\Delta)\mathrm{d}F\left(\Delta\right).$$

Using the definition (2.6) of the reservation productivity of counseled unemployed workers, one gets equation (2.7).

not counseled given that an unemployed workers has been met is defined by :

$$\alpha = \frac{u_0}{u_1\delta + u_0}.$$

When a worker is met, he is thus counseled with probability $1-\alpha$. Non counseled job seekers accept any job offer whereas counseled job seekers only accept job whose duration is longer than Δ_1. Accordingly, the value of a vacant job satisfies

$$r\Pi_v = -h + m\left(\theta\right)\left(\alpha\int_0^{+\infty}\Pi\left(\Delta\right)\mathrm{d}F\left(\Delta\right) + \left(1-\alpha\right)\int_{\Delta_1}^{+\infty}\Pi\left(\Delta\right)\mathrm{d}F\left(\Delta\right)\right). \quad (2.9)$$

The free entry condition, $\Pi_v = 0$, implies, together with equations (**??**) and (**??**), that

$$\frac{h}{m\left(\theta\right)} = \left(\alpha\int_0^{+\infty}\gamma\left(\Delta\right)\mathrm{d}F\left(\Delta\right) + \left(1-\alpha\right)\int_{\Delta_1}^{+\infty}\gamma\left(\Delta\right)\mathrm{d}F\left(\Delta\right)\right)\left(y-w\right). \quad (2.10)$$

The free entry condition can be interpreted as a labor demand equation that relates the labor market tightness θ to the reservation duration of counseled job seekers.The labor market tightness decreases with the reservation duration on the labor demand curve because employers face a higher probability to meet a worker who refuses job offers when the reservation duration is higher. Since the arrival rate of job offers to the non counseled workers, equal to $\theta m(\theta)$, increases with the labor market tightness, a raise in the reservation duration of counseled unemployed workers has a negative impact on the job arrival rate of the non counseled unemployed workers.

In steady state equilibrium, the flows of entries into and exits from counseled unemployment are equal :

$$\mu u_0 = \lambda_0 \bar{F}(\Delta_1)\delta u_1,$$

where $\bar{F} = 1 - F$, thus

$$\alpha = \frac{\lambda_0\bar{F}(\Delta_1)}{\lambda_0\bar{F}(\Delta_1)+\mu}. \quad (2.11)$$

Let us assume that the matching function takes the form $m_0 s^{\eta} v^{1-\eta}$, $\eta \in (0,1)$, $m_0 > 0$. This implies that $m(\theta) = m_0 \theta^{-\eta}$. Then, from $\lambda_0 = \theta m(\theta)$, we get $m(\theta) = m_0^{1/(1-\eta)} \lambda_0^{-\eta/(1-\eta)} = \Lambda \lambda_0^{-\sigma}$.

Using the value of α defined in equation (2.11), the free entry condition (2.10) can be written as a relation between λ_0, the arrival rate of job offers to the non counseled job seekers and Δ_1, the reservation productivity of counseled workers :

$$\frac{h}{(y-w)\Lambda} = \lambda_0^{-\sigma} \left(\frac{\mu}{\lambda_0 \bar{F}(\Delta_1) + \mu} \int_{\Delta_1}^{+\infty} \gamma(\Delta)\, \mathrm{d}F(\Delta) + \frac{\lambda_0 \bar{F}(\Delta_1)}{\lambda_0 \bar{F}(\Delta_1) + \mu} \int_0^{+\infty} \gamma(\Delta)\, \mathrm{d}F(\Delta) \right). \tag{2.12}$$

2.2.3 The equilibrium

The equilibrium values of the two unknown variables λ_0 and Δ_1 are defined by the solution to the system of equations (2.7) and (2.12), where r, δ, $F(.)$, h, π, Λ, σ and μ are parameters.

The existence of an equilibrium can easily be proved. The labor supply equation (2.7), which is depicted on figure 2.2, defines an increasing relation between λ_0 and Δ_1 with $\lambda_0 \to 0$ when $\Delta_1 \to 0$ and $\lambda_0 \to +\infty$ when $\Delta_1 \to +\infty$. The labor demand equation (2.12) defines a relation between λ_0 and Δ_1, with $\lambda_0 \to 0$ when $\Delta_1 \to +\infty$ and $\lambda_0 \to \lambda_{00}$ when $\Delta_1 \to 0$, where λ_{00} is the counterfactual equilibrium job offers arrival rate in the absence of the policy ($\mu = 0$), which is merely given by :

$$\frac{h}{(y-w)\Lambda} = \lambda_{00}^{-\sigma} \int_0^{+\infty} \gamma(\Delta)\mathrm{d}F(\Delta) \tag{2.13}$$

Therefore, the labor demand and the labor supply equation intersect at least once as it is illustrated on figure 2.2.

The labor demand equation (2.12) does not always define a negative relation between λ_0 and Δ_1. Accordingly, the unicity of the equilibrium is not always fulfilled. However, it will be checked that the unicity of the equilibrium is fulfilled for the

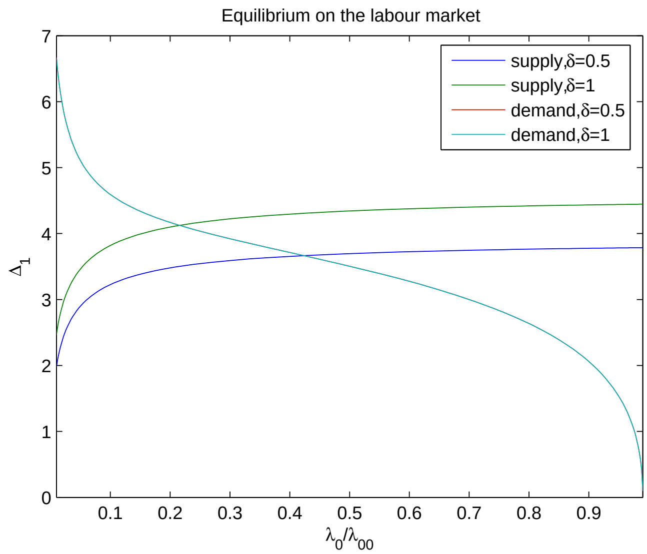

FIG. 2.1 – Equilibrium on the labor market

FIG. 2.2 – Labor supply and labor demand equation.

values of the paramaters that are estimated.

Knowledge of the parameters of the model will allow us to compute the equilibrium value of the arrival rate of job offers in the absence of counseling, denoted by λ_{00}, which is defined in equation (2.13). In particular, the effect of counseling on the non counseled job seekers is measured by λ_0/λ_{00}. The model allows us to analyze more generally the consequence of counseling on labor market equilibrium.

On another hand, an increase in μ, the rate of entry into counseling, moves upwards the labor supply curve depicted on figure 2.2 : unemployed workers accept jobs with lower duration when the rate of entry into counseled unemployment is higher. This relation can be understood as follows. Counseling creates an opportunity cost of accepting job offers because workers are not counseled any more when they are employed. And once counseled job seekers lose their job, they will have to wait a while before receiving counseling again. The opportunity cost of accepting a job offer is thus lower when the waiting period to come back into counseling is shorter (higher

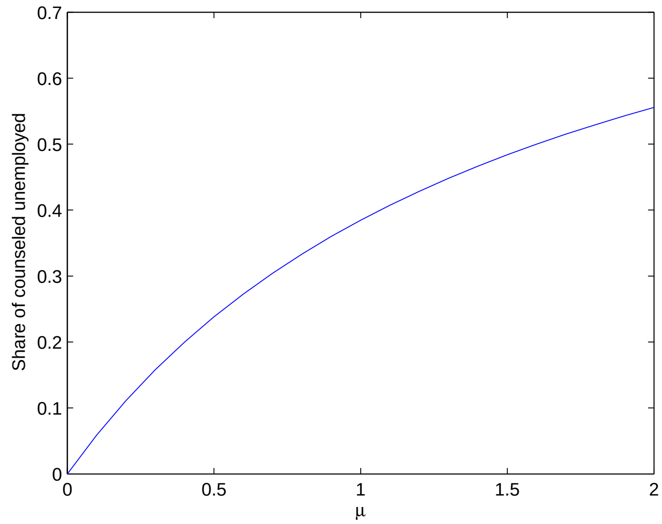

FIG. 2.3 – The impact of counseling on the share of non treated among the unemployed

μ). Since a lower opportunity cost of accepting jobs implies a lower reservation utility, this phenomenon implies that the reservation utility of counseled job seekers decreases with the share of workers who benefit from counseling. In the limit, when all job seekers are counseled, the opportunity cost of accepting a job goes to zero, because the waiting period before coming back into counseling after a job-loss goes to zero.

An increase in the rate of entry into counseling moves the labor demand curve downwards : firms create less job vacancies when a larger share of job seekers are counseled because the probability to meet a worker who refuses job offers is higher.

These changes in labor supply and labor demand imply that the spread of counseling always reduces the reservation duration of counseled job seekers. However, the impact of spreading out counseling on the baseline arrival rate of job offers $(\lambda_0 = \theta m(\theta))$ has ambiguous sign. As shown by Figure 2.3, the relation between the entry rate into counseling and the arrival of job offers is U-shaped : increases in μ

reduce the arrival rate of job offers when the entry rate is small. The opposite holds true when the entry rate is large. Moreover, in the limit, the arrival rate of job offers *to the non counseled workers* is identical when the share of counseled workers goes to 1 and in the absence of counseling, since the reservation duration is equal to zero in both cases. Naturally, if *all* workers are treated upon entering unemployment, the equilibrium exit rate that applies to the economy is higher than when counseling is absent, because search efficiency is higher, everything else equal - *thus the effect on overall exit rate is rather J-shaped.*

2.3 Econometric implementation

Assessing the equilibrium impact of the policy in this model, and the effect of changing the policy intensity, requires knowledge of all parameters. They can be estimated based on data about : (1) unemployment duration until counseling, (2) unemployment duration until employment and (3) employment duration. The informal identification argument is as follows. Treatment intensity (μ) can be obtained from the first duration. The second duration contains information on λ_0, and comparing treated and untreated is informative on δ. The distribution of employment duration $F(.)$ can be inferred from the third duration and, again, comparing treated and untreated is informative on Δ_1, which is the only source of employment duration difference between the two groups. The discount rate is not estimated, it is set to $r = 0.05$.

This set of parameters can be constrained to fit the labor supply curve defined by equation (2.7).[4] The labor demand curve, equation (2.12), still depends on two additional unknown parameters, σ and $h/(y-w)\Lambda$. We choose to set $\sigma = 1$ (and test for robustness of the results over the range 0.75-1.25). Then, knowledge of the equilibrium point (λ_0, Δ_1) in figure 1 identifies the parameter $h/(y-w)\Lambda$, thus λ_{00}.

[4]Given r, this is an equality constraint over the parameters.

As there is no information to disentangle h, y, w and Λ, we set $R = h/(y-w)\Lambda$ and estimate R directly. This latter parameter can be interpreted as the inverse of a 'return' to job creation (the profit $(y-w)$ weighted by baseline market efficiency $\Lambda = m_0^{1/(1-\eta)}$, relative to the cost h) : markets with higher R tend to have a lower demand curve.

We assume that the distribution $F(.)$ can be parametrized as

$$F(\Delta) = 1 - e^{-\eta\Delta}$$

implying that the employment duration has a constant hazard η. Notice that duration until counseling also has constant hasard μ. As a result, λ_0 doesn't have duration dependance either. Including non-stationarity in such an empirical structural model would be a formidable task. As will appear, *observed* duration dependence will be accounted for by unobserved heterogeneity.

In order to account for observed and unobserved heterogeneity, we group data into cells defined by a set of observed characteristics (X =region, education, age and sex) and we assume that, within each cell, unobserved heterogeneity can be captured by a random variable, distributed on a discrete support. We further assume that each group defined by a set of observed characteristics *and* a value of unobserved heterogeneity forms a distinct 'job market', over which equations (2.7) and (2.12) hold. In this setup, we have to face the usual problem that treatment parameters δ and $F(\Delta_1)$ can be counfounded with unobserved heterogeneity : a group that is intrinsically more efficient at job search may be also treated less often, so that direct comparison of unemployment durations across treated and untreated would, in this example, understate the true policy parameter δ. However, it is well known that, in the mixed proportional hasard model, this parameter is non-parametrically identified (Abbring and van den Berg, 2003). Our model differs from this standard setup, but identification is proved in appendix A. The constant hasards hypothesis plays an important role in this proof, as *observed* duration dependance helps identify unobserved heterogeneity.

The model is estimated separately for cells defined by observed characteristics. We call t_U total unemployment duration, t_T unemployment duration until entry into treatment and t_E employment duration. In a given market (conditional on X and ε), the likelihood has the following expressions (where all parameters, but r and σ, are specific to market (X, ε), which is kept implicit for legibility) :

– If treatment occurs before exit to employment $(t_T < t_U)$:

$$L(t_U, t_T, t_E|X, \varepsilon) = \mu \left[\lambda_0 \delta \overline{F}\left(\Delta_1\right)\right]^{c(U)} e^{-([\lambda_0+\mu]t_T+\lambda_1[t_U-t_T])} \left[\eta^{c(E)} 1_{t_E>\Delta_1} e^{-\eta(t_E-\Delta_1)}\right]^{c(U)}$$

– If exit to employment occurs before treatment $(t_T = t_U)$:

$$L(t_U, t_T, t_E|X, \varepsilon) = \lambda_0^{c(U)} e^{-([\lambda_0+\mu]t_U)} \left[\eta^{c(E)} e^{-\eta t_E}\right]^{c(U)}$$

where $c(U) = 0$ when the unemployment spell is censored and 1 otherwise and $c(E) = 0$ when the employment spell is censored and 1 otherwise. We also impose the two restrictions derived from equations (2.7) and (2.12), which implicitly define the two endogenous variables within each market :

$$\lambda_0 \left(\delta, \sigma, \mu, R, \eta\right)$$
$$\Delta_1 \left(\delta, \sigma, \mu, R, \eta\right)$$

The observable likelihood then has the following expression :

$$L(t_U, t_T, t_E|X) = \int L(t_U, t_T, t_E|X, \varepsilon) dH(\varepsilon; \pi)$$

where $H(\varepsilon; \pi)$ is the distribution of unobserved heterogeneity and π its parameters. Heterogeneity applies to μ, R and η and is specified with two factor loadings :

conditional on X they have values

$$\mu = \exp(\pi_\mu^1), R = \exp(\pi_R^1), \eta = \exp(\pi_\eta^1)$$

with probability p and values

$$\mu = \exp(\pi_\mu^2), R = \exp(\pi_R^2), \eta = \exp(\pi_\eta^2)$$

with probability $1-p$. This specification ensures that μ, R and η can be correlated in an unconstrained manner. For instance, unobserved features can make treatment μ more intensive in markets that have longer contracts (η).

For tractability reason we split our sample into cells over which estimations are run separately. As explained above a cells is a set of spells sharing the same region/education/age/sex. A 'market' will be the set of spells sharing the same region/education/age/sex and the same unobserved type. Thus there are two 'markets' in each cell. We estimate the maximum likelihood above as a constrained parametric duration model with finite mixture using the software KNITRO AMPL. This estimation provides us with a set of parameters by unobserved types : in other words we end up with an estimate by 'market'. Then we work out MLE variance through MATLAB.
As the likelihood is not differentiable in Δ_1, we smooth it by replacing the dummy function $t_E - \Delta_1 > 0$ with a logistic function $\frac{1}{1+exp(-6*(t_E-\Delta_1))}$ The estimation lasts 5 nearly days. A few cells (less than 5) shows convergence issues.

The distribution of parameters over all markets can then be presented non-parametrically. In order to have a more structured view of the results, we can also project the parameters linearly over the region/education/age/sex variables, so as to describe the effects of observable characteristics on the various durations.

Based on the estimates, we can then compute a set of evaluation parameters and counterfactuals. In each case, there are as many effects as there are markets. In this sense, our specification is very flexible with respect to heterogeneity of treatment effects. The main effects we are interested in are the following :

- The effect of the policy on the non-treated : the exit rate from unemployment for the non treated λ_0 compared with the exit rate λ_{00} that would prevail if the policy did not exist ($\mu = 0$). This is a measure of the policy spillover on the untreated.
- The direct effect of the treatment : the treated net exit rate from unemployment, $\lambda_0 \delta e^{-\eta\Delta_1}$ compared with the exit rate λ_0 of the non treated.
- The equilibrium effect of the treatment on the treated : $\lambda_0 \delta e^{-\eta\Delta_1}$ compared with the exit rate λ_{00} in the absence of the policy.
- The effect of the policy on unemployment duration : the expected duration (*ex ante* i.e. either treated or non treated) compared with the counterfactual expected duration in the absence of the policy ($\delta = 0$).

2.4 Data

The empirical analysis is based on administrative longitudinal data extracted from the records of the French public unemployment service (ANPE). We use unemployment inflow since July 2001, when counseling schemes where introduced at a significant scale as part of the so-called *Plan d'Aide au Retour à l'Emploi*. During a compulsory meeting, the unemployed person and the caseworker come to an agreement over the degree of assistance that the person should receive. Depending on this evaluation and available spots, the unemployed may be subsequentely offered a scheme. We count as treatment two categories of schemes : a basic *Skill assessment* and a *Job-search support*, aimed at directly helping individuals on their search actions. Although there is sufficient data to analyze those schemes separately (Crépon et al. 2005), we bunch them into a unique treatement. We use a 1/12 nationally representative sample of all unemployed persons registered with ANPE.[5] We sample all inflow spells since July 2001 and data end in June 2004. We also truncate spells when the unemployed reaches 55 year-old. The average unemployment rate is high (36 percent) because our data cover individuals registered at the ANPE at least once between July 1001 and June 2004.

Entry into and exit from unemployment are recorded on a daily basis, so that we model duration in continuous time. In this data, unemployment differs from the ILO conventional notion, in the sense that people are recorded as job seekers as long as they report so to ANPE on a monthly filled form, even if they have held occasional or short-term jobs, which they have to declare. As a result, we have reconstructed unemployment spells to account for the fact that a job is found, even if the individuals still reports himself as a job-seeker to the administration. In practice, we end the spell when the individuals either exits for good or holds such a short-term job, provided he worked at least 78 hours in the month. The exact date of employment is not declared in that case and we compute it as if reported hours where worked full time at the end of the period. When this occasional employment stops, we start a new spell (with the same kind of conventional starting date), and so on. We end up with a sample of 479,334 individuals for 981,901 unemployment spells overall.

Transitions may occur towards other destinations than employment but they are be treated as censoring, which implies that they depend upon a disjoint subset of parameters. Although undesirable in some instances, this hypothesis maintains tractable estimation. "Other destinations" include training, illness, inactivity and, most importantly, subsidized public employment. In addition, some unemployed do not send their monthly form at some point so that they are known to exit but the

[5]The sample consists of all individuals born on March of an even year or October of an odd year. This sample, named "Fichier historique statistique" is updated routinely by ANPE.

destination is unobserved. Estimation is limited to individuals with known exit.

As we have no direct information on employment periods, we proxy employment duration with the time between an exit to employment and a new unemployment spell. We have 552,508 such employment spells.

ANPE also provided data on the services that benefited each unemployed worker in the sample, with a date for the effective beginning of the scheme. This has been matched with the data on unemployment spells. Out of the 981,901 unemployment spells, 62,941 received counseling. Note that, when we split administrative spells into a series of effective spells separated by short-term jobs, we maintain the treatment status only for the effective spells in effect when treatment started.

2.5 Results

We first present the estimated parameters, and specifically their distribution accross the "markets". Then, we evaluate the impact of counseling on transitions between unemployment and employment. Finally, we analyze the effect of counseling on unemployment rates.

2.5.1 Estimated parameters

Parameters are estimated by maximum likelyhood independently on cells assumed to represent distinct labor markets differentiated by sex, age, education and region. We only retain the 1562 cells with 41 or more observations. The largest cell contains 7676 observations. Table 2.1 gives a few statistics on these cells.

Table 2.2 gives the mean value of the following parameters :[6] the rate of entry into counseling (μ), the exit rate out of employment (η), the baseline arrival rate of job offers (λ_0), the reservation employment duration of counseled job seekers (Δ_1),

[6] We compute the average values of the parameters estimated on each labor market. Each observation is weighted by the size of the corresponding market.

the direct impact of counseling on the arrival rate of job offers (δ), the exit rate out of employment of counseled job seekers ($\delta\lambda_0\bar{F}(\Delta_1)$) and the value of the counterfactual arrival of job offers in the absence of counseling (λ_{00}).

The average entry rate into counseling is 0.22. This is a very low rate of entry which implies that unemployed workers have to wait on average about four years and seven months to benefit from counseling. It should be noticed that the observed average unemployment duration necessary to enter into counseling is smaller since most unemployed workers find a job before four years and seven mounths. Actually, the average unemployment duration of non counseled job seekers ($1/\lambda_0$) is about seven months.

The average unemployment duration of counseled job seekers (equal to $1/\lambda_1$) is 2.2 percent smaller than the average unemployment duration of those who are not counseled. The difference between the arrival rates of job offers to counseled and non counseled individuals is much bigger since it is 15.6 percent higher for counseled individuals.[7] Therefore, the relative small difference between unemployment spells of counseled and non counseled job seekers is explained to a large extent by the fact that counseled individuals refuse short term contracts whereas non counseled job seekers accept all jobs, as shown in the theoretical model. The estimated value of Δ_1 implies that counseled workers refuse, on average, jobs whose duration is smaller than 0.21 year

Table 2.2 also sheds some light on the equilibrium effects of counseling. It shows that the average effect of counseling on the arrival rate of job offers to non counseled workers is weak : the baseline arrival rate of job offers (λ_0) is 1.2 percent smaller than the counterfactual arrival rate of job offers in the absence of counseling (λ_{00}). However, compared with the difference between the exit rate of counseled individuals and those who are non counseled, which amounts to 2.8 percent, this number is not

[7]This difference is captured by parameter δ.

negligeable.

The densities of the parameters whose average value is presented in Table 2.2 are displayed on Figures 2.4, 2.5, 2.6, 2.7, 2.8 and 2.9. It turns out that the densities of the job loss rate (η) and of the two exit rates out of unemployment (λ_0 and $\delta\lambda_0\bar{F}(\Delta_1)$) are clearly bimodal. This illustrates the well documented dual feature of the French labor market where some workers have access to stable jobs that benefits from a strong employment protection and other workers are constrained to accept fixed term contracts associated with shorter employment spell. Table 2.3 gives the distribution of these parameters per centiles.

Table 2.4 documents the relation between the estimated parameters and the features of labor markets. In this table we regress the values of the maximum likelihood estimates of the parameters on the cells characteristics (gender, age, education, region). This table shows that women, young workers and people with low education have shorter employment spells than other people. The exit rates out of unemployment of men and women are not statistically different. Individuals with high levels of education, above high school, exit faster out of unemployment than those without any diploma. It also appears that unemployment duration increases with age. Table 2.4 also shows that counseling does not always contribute to help the most disadvantaged : although women tend to receive counseling more often (2 percent) than do men, people with medium academia standards (finishing high school) are the most often treated. Counseling is the most frequent at mid-career (30-50 year-old).

2.5.2 The effects of the policy on transitions between employment and unemployment

Standard evaluations, relying on a simple comparison of the outcome of the treated and the non treated, can lead to wrong results if the policy induces equilibrium effects that change the arrival rate of job offers λ_0. The error comes from the choice

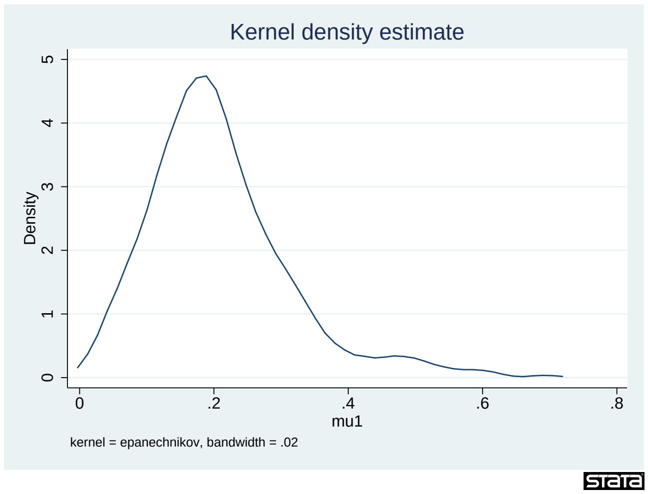

FIG. 2.4 – Density of the rate of entry into counseling μ.

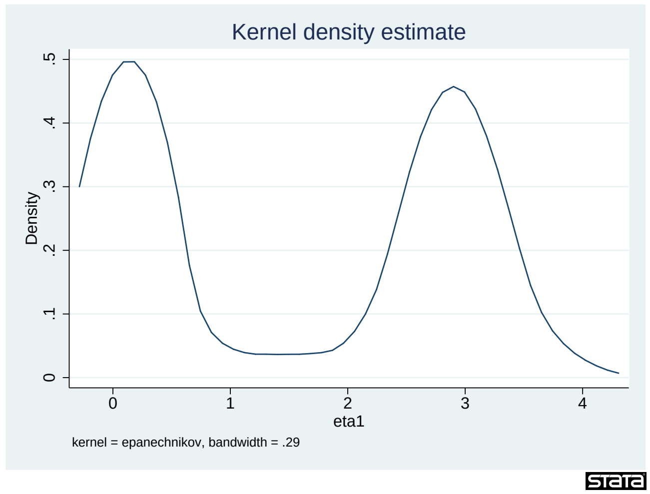

FIG. 2.5 – Density of the exit rate out of employment η.

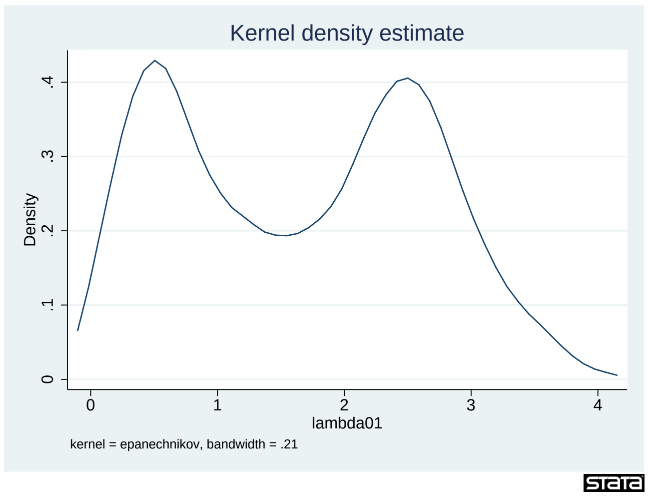

FIG. 2.6 – Density of the exit rate out of unemployment of non counseled workers λ_0.

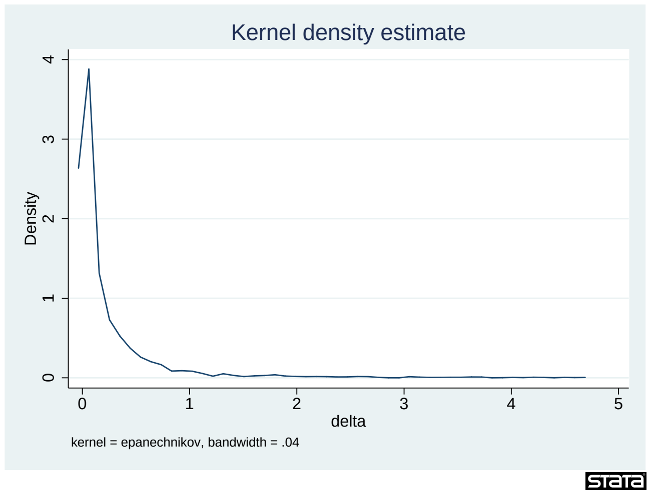

FIG. 2.7 – Density of the direct impact of counseling on the arrival rate of job offers δ.

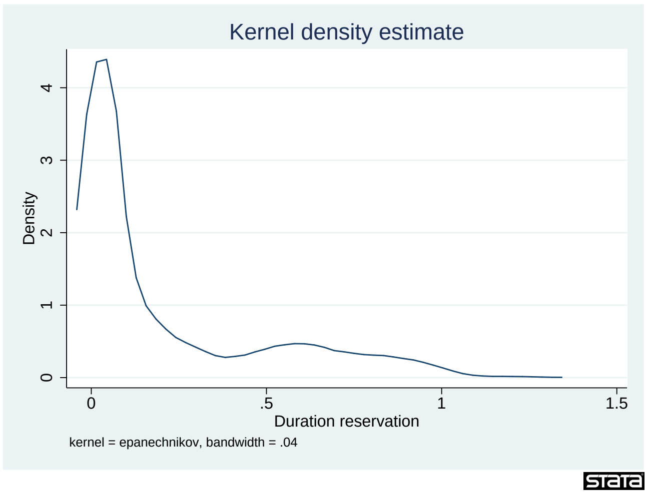

FIG. 2.8 – Density of the reservation duration Δ_1.

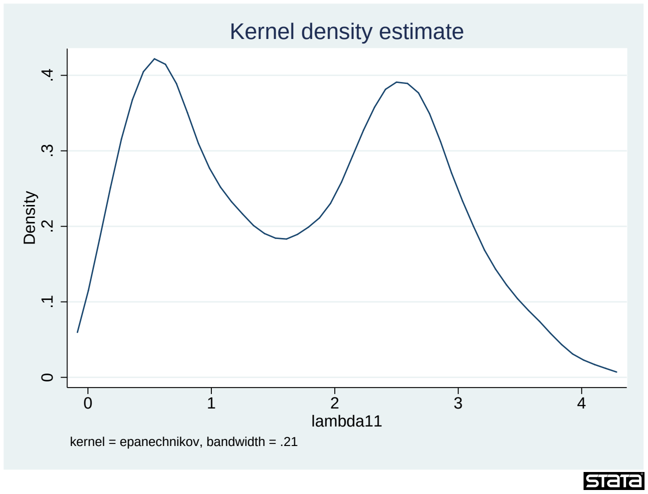

FIG. 2.9 – Density of the exit rate out of unemployment of counseled job seekers $\delta\lambda_0\overline{F}(\Delta_1)$.

of wrong counterfactuals when evaluating the impact of the policy : standard evaluations assume that the counterfactual arrival rate of job offers and the reservation employment duration in the absence of the policy are the same as those observed by the econometrician in the presence of the policy for the untreated, whereas the 'true' counterfactuals are different. In our model, the exit rate out of unemployment of counseled job seekers amounts to $\delta\lambda_0\bar{F}(\Delta_1)$. Non treated individuals exit unemployment at rate λ_0. The effect of the treatment on the treated is usually defined as the ratio between these two exit rates, that is $\delta\bar{F}(\Delta_1)$. However, this approach yields a naive evaluation of the effects of the treatment to the extent that it does not account for equilibrium effects which may change the value of the arrival rate of job offers to the non counseled job seekers. To account for such effects one needs to know the exit rate out of unemployment in the absence of counseling, that is λ_{00}. Then, the effect of the treatment on the treated accounting for equilibrium effects is defined as $\delta\lambda_0\bar{F}(\Delta_1)/\lambda_{00}$. The error induced by the ignorance of equilibrium effects, expressed in percentage of the impact of the treatment not accounting for equilibrium effects, is thus $(\lambda_0 - \lambda_{00})/\lambda_{00} \simeq \ln(\lambda_0/\lambda_{00})$. Our empirical strategy allows us to estimate this error.

The naive evaluation of the effect of counseling on counseled workers The evaluation of the impact of the treatment on the exit rate out of unemployment of counseled workers with no account of equilibrium effects, $\delta\bar{F}(\Delta_1)$, is 3.5 percent on average. It is different across labor markets. The density of the naive evaluation of the effect of counseling is displayed on figure 2.10. The orders of magnitude of the estimates are in line with those of Crepon et al. (2005).

As shown by Table 2.4, the impact of counseling depends on observed individual characteristics : the treatment is 5.7 percent stronger for women. The treatment is significantly stronger for persons without diploma than for people with some high school and with diploma. The impact of age is either very small or not significant.

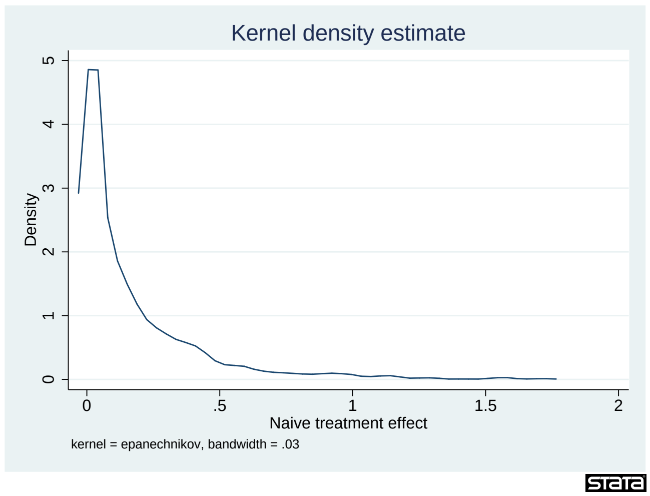

FIG. 2.10 – Density of the effect of counseling on the treated $\delta\bar{F}(\Delta_1)$

The exit rate out of unemployment of non counseled workers and the evaluation error In our model, the policy lowers the arrival rate of job offers to the non counseled, λ_0, compared to the rate that would prevail in the absence of the policy, λ_{00}. Figure 2.11 displays the density of the term $\ln(\lambda_0/\lambda_{00})$ which measures, on each labor market, the impact of the policy on the exit rate of non counseled workers expressed in percentage of their exit rate in the absence of the policy. It is also worth noting that the term $\ln(\lambda_0/\lambda_{00})$ measures the size of the evaluation error due to the ignorance of equilibrium effects.

On average, the arrival rate of job offers to non counseled job seekers is reduced by 1.2 percent only by the policy. Since the average evaluation error is small, accounting for equilibrium effects does not change much the average estimated effects of counseling on the exit rate out of unemployment of the treated. However, there are strong differences across labor markets as it is illustrated by Figure 2.11. The vertical axis reports the impact of counseling on the exit rate out of unemployment of the non treated $\ln(\lambda_0/\lambda_{00})$. The horizontal axis corresponds to the rate of entry into counseling. Figure 2.11 shows that the effects of counseling on the non treated is different across labor markets. These effects can be quite large, reducing the exit rate out of unemployment of non counseled by up to 7 percent. It turns out that the magnitude of the impact is stronger in labor markets where the entry rate into counseling is lower, according to the prediction of our model.

It should also be noticed, as shown in table 2.4, that the magnitude of the negative impact of the policy on the exit rate out of unemployment of the non treated is 10 percent stronger for women. The negative impact is also stronger for individuals without diploma. This result suggests that the most disadvantaged people are those who suffer the most from the crowding out effects of counseling.

The effect of the policy on employment duration Counseling changes the employment reservation duration of counseled workers. The non counseled accept all

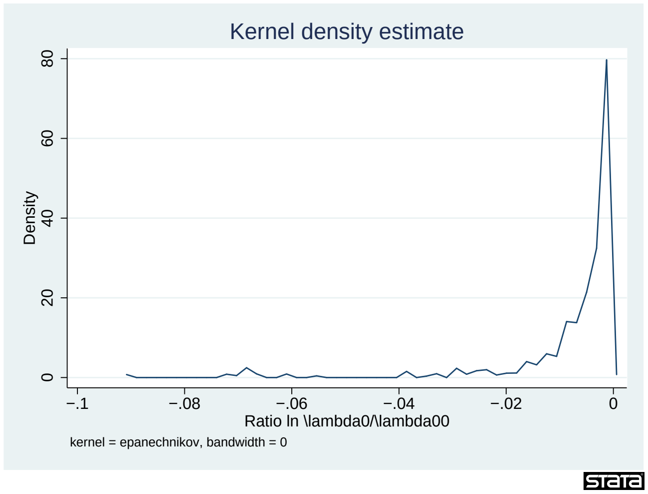

FIG. 2.11 – Density of the ratio $\frac{\lambda_0}{\lambda_{00}}$

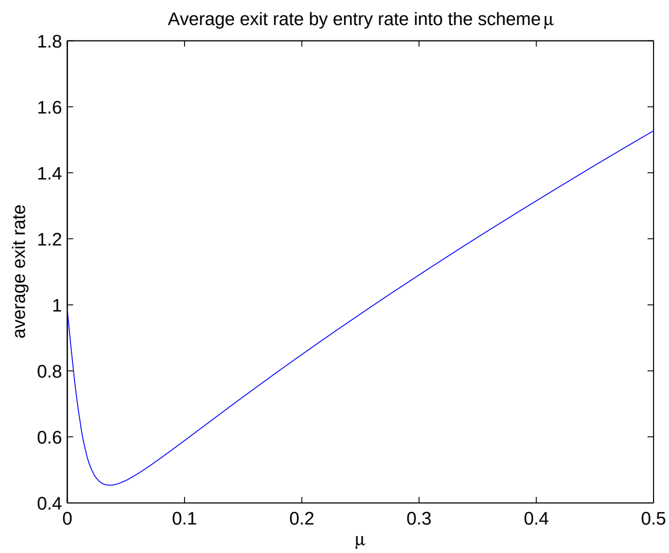

FIG. 2.12 – The impact of counseling on the exit rate of the non treated

jobs, whereas the counseled accept jobs whose duration is above the threshold Δ_1. Figure 2.9 displays the density of the reservation duration. Counseling has a strong positive impact on the reservation duration of counseled job seekers. Accordingly, the employment duration is longer for the counseled than for the non counseled.

2.5.3 Measuring the effect of counseling on unemployment rate

Counseling changes the unemployment rate through its effects on the search efficiency, δ, and the reservation duration, Δ_1, of counseled workers, but also through its impact on the arrival rate of job offers λ_0. The choice of wrong counterfactuals can lead to different type of evaluation errors of the impact of the policy on unemployment.

Let us denote by $u(\delta, s, \lambda_0, \Delta_1)$ the unemployment rate, which depends on δ, the job search efficiency of counseled workers, on s, the share of counseled job seekers, on λ_0, the arrival rate of job offers and on Δ_1, the employment reservation duration. This unemployment rate can be computed as the stationary equilibrium rate, based on our structural model, at estimated parameters.

Naive evaluations compute the impact of the policy with the assumption that the arrival rate of job offers and the reservation duration remain unchanged in the absence of the policy. Then, the counterfactual unemployment rate is $u(\delta, 0, \lambda_0, \Delta_1)$, whereas the 'true' counterfactual should be evaluated with λ_{00} and with a reservation employment duration equal to zero, i.e. it should be $u(\delta, 0, \lambda_{00}, 0)$. Figure 2.13 shows the values of the impact of the policy on the unemployment rate computed with the true counterfactual (i.e. $\ln[u(\delta, s, \lambda_0, \Delta_1)/u(\delta, 0, \lambda_{00}, 0)]$) depending on the value of unemployment without the policy, $u(\delta, 0, \lambda_{00}, \Delta_1)$. We can see that, for most 'markets', the unemployment decrease resulting from the actual level of the policy is less than 2 points, but it tends to be stronger for high unemployment 'markets'. On average, the unemployment rate is reduced by 1.4 percentage point, dropping from 36.3 percent to 35.9 percent.

Figure 2.14 displays the density of the error we would make if we compared the actual unemployment rate with a stationary rate computed at λ_0 and Δ_1 equilibrium values. The bias is then equal to $\ln[u(\delta, 0, \lambda_0, \Delta_1)/u(\delta, 0, \lambda_{00}, 0)]$. Not accounting for equilibrium effects leads to overestimate the impact of counseling on the unemployment rate by 4.1 percent on average, because counseling reduces the exit rate out of unemployment of non counseled job seekers. This is a relatively small figure. However the error can be much larger on some labor markets as previously shown.

Another error can be made when simulating the consequence of the spread of the policy to all workers. Looking at this type of error is important to the extent that some policy makers think that policies should first be evaluated at a small scale before being generalized if their evaluations are favorable. This idea is right only if equilibrium effects are properly taken into account. Ignoring such effects can

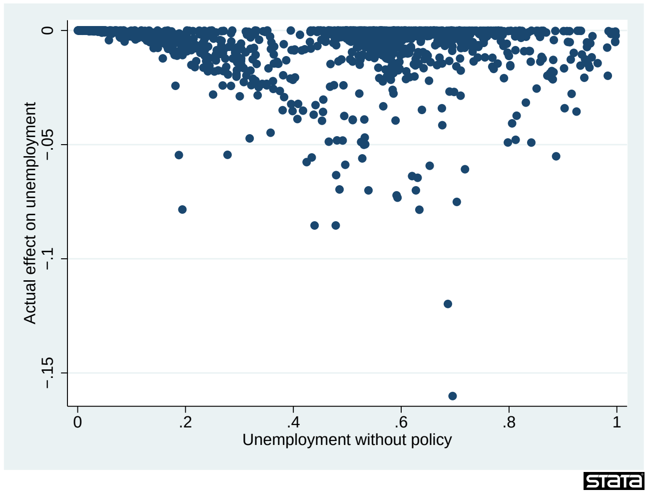

FIG. 2.13 – The impact of counseling on the unemployment rate in each labor market computed with the true counterfactual (i.e. $u(\delta, s, \lambda_0, \Delta_1)/u(\delta, 0, \lambda_{00}, 0) - 1$) depending on the value of unemployment without the policy, $u(\delta, 0, \lambda_{00}, \Delta_1)$.

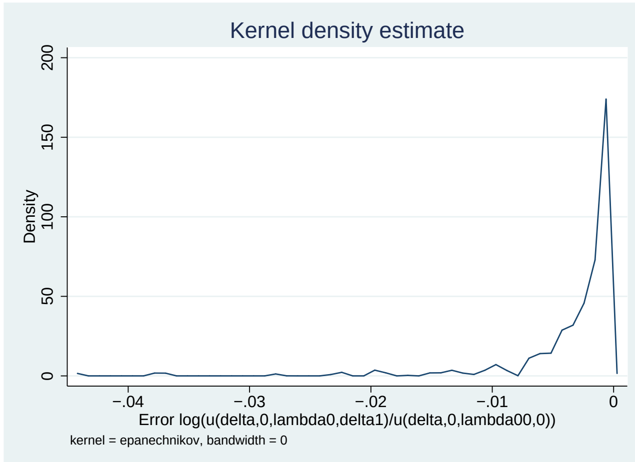

FIG. 2.14 – Density of the evaluation error of the impact of counseling on the unemployment rate.

lead to false conclusions, because it is wrong to simulate the impact of the generalization of counseling to all job seekers with the assumption that the arrival of job offers and the reservation employment duration remain unchanged. Evaluation of the unemployment rate impact of expanding the policy completely is presented on Figure 2.15 which plots $\ln[u(\delta, 1, \lambda_{00}, \Delta_1)/u(\delta, 0, \lambda_{00}, 0)]$, again depending on unemployment without the policy. The effects are now much stronger, and again larger for high unemployment 'markets'.

When the impact of the policy is evaluated without accounting for equilibrium effects, the estimated change in the unemployment rate induced by counseling all workers, compared to the situation without counseling, is $D_0 = \ln[u(\delta, 1, \lambda_0, \Delta_1)/u(\delta, 0, \lambda_0, \Delta_1)]$. The density of the error induced by the ignorance of equilibrium effects when one simulates the impact of the spreading of counseling to all workers is displayed on Figure 2.16. Ignoring equilibrium effects leads to underevaluate the impact of the generalization of counseling because the baseline arrival rate of job offers λ_0 is always higher when all job seekers are counseled than when only a fraction of them benefit from counseling (as shown by figure 2.3). On average, the reduction of unemployment entailled by the generalization of counseling to all job seekers is underevaluated by 0.4 percent. Once again, this figure is relatively small, but it can be much bigger on some labor markets.

2.6 Conclusion

Our analysis of equilibrium effects of job search counseling provides some striking insights.

First, evaluation errors made when equilibrium effects are not accounted for can lead to misleading conclusions even when the treatment group is small. For instance, naive evaluations based on differences in exit rate out of unemployment of treated and non treated individuals may conclude that counseling increases the average exit

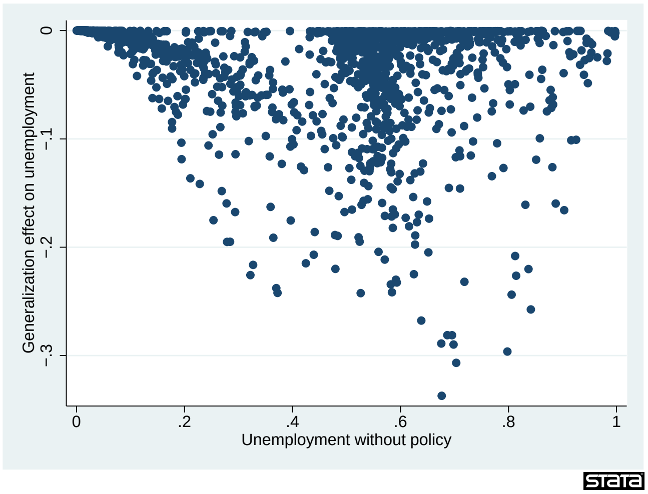

FIG. 2.15 – The change in the unemployment rate induced by counseling all workers depending on the value of unemployment without the policy.

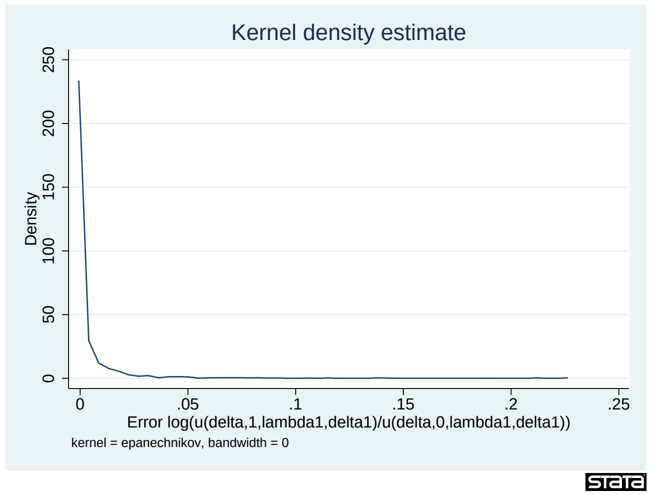

FIG. 2.16 – Evaluation error of the impact of counseling all workers on the unemployment rate

rate out of unemployment although the right conclusion can be opposite even when the share of counseled job seekers is close to zero.

Second, equilibrium effects of counseling are not monotonous : spreading counseling to more job seekers has a negative impact on the exit rate out of unemployment of non counseled job seekers when the share of counseled workers is small, and this impact becomes positive when the share of counseled workers is large enough. The non monotonicity stems from the interactions of labor supply and labor demand reactions.

Our approach also allows us to show how equilibrium effects vary across labor markets. They are more important for workers who are more at the margin of the labor market, like women and less skilled workers.

These results have important policy implications. They obviously show that it is important to account for equilibrium effects to correctly evaluate policies. The non monotonicity of the equilibrium effects of counseling and its potential positive impact on unemployment also implies that it can be worthless counseling a small share of job seekers but worth counseling a large share of job seekers.

Though many questions will need to addressed in the future. On the methodological side identification and robustness must be checked. On the public policies side our analysis is limited to microeconomic effects on the unemployed with no respect for what the measure may cost for the public employment service. Therefore it is difficult at this stage to carry out a full cost-benefit analysis.

2.7 Appendix

2.7.1 Identification

The model defines λ_0, Δ_1 and $\lambda_1 = \lambda_0 \delta \overline{F}(\Delta_1)$, as functions of parameters δ and σ, and values of μ, R and η, which contain heterogeneity terms. We have

$$\begin{aligned}
\lambda_0 &= \lambda_0(\delta, \sigma, \mu, R, \eta) \\
\Delta_1 &= \Delta_1(\delta, \sigma, \mu, R, \eta) \\
\lambda_1 &= \lambda_1(\delta, \sigma, \mu, R, \eta) = \lambda_0(\delta, \sigma, \mu, R, \eta)_0 \, \delta e^{-\eta \Delta_1(\delta, \sigma, \mu, R, \eta)}
\end{aligned}$$

We reset these parameters as $x = \lambda_0 + \mu$, $y = \lambda_1$ and $z = \eta$. Likewise we can express :

$$\begin{aligned}
\mu &= \mu(\delta, \sigma, x, y, z) \\
\lambda_0 &= \lambda_0(\delta, \sigma, x, y, z) = x - \mu(\delta, \sigma, x, y, z) \\
\lambda_1 &= y \\
\Delta_1 &= \Delta_1(\delta, \sigma, x, y, z) = \left(\log(x - \mu(\delta, \sigma, x, y, z)) - \log\left(\frac{y}{\delta}\right)\right) \Big/ z \\
R &= R(\delta, \sigma, x, y, z) \\
\eta &= z
\end{aligned}$$

The data identifies the probability of transition at different time :

$$\begin{aligned}
p(t_t, t_R, t_E) &= \int \mu \lambda_1 \eta \exp\left(-(\lambda_0 + \mu) t_T - \lambda_1 t_R - \eta(t_E - \Delta_1)\right) H(t_E - \Delta_1) \, \mathrm{d}G(x, y, z) \\
&= \int \exp(-x t_T - y t_R - z t_E) \, \mu(\delta, \sigma, x, y, z) \, yz \exp(z \Delta_1(\delta, \sigma, x, y, z)) \ldots \\
&\quad \ldots H(t_E - \Delta_1) \, g(x, y, z, \sigma, \delta) \, \mathrm{d}x \mathrm{d}y \mathrm{d}z
\end{aligned}$$

where H is the Heavyside function, t_T is the date of treatment, $t_R = t_U - t_T$ the residual duration in unemployment in case of treatment and t_E the employment duration.

Recalling the injectivity of Laplace transform, for given δ and σ we identify the function $\mu(\delta,\sigma,x,y,z)\,yz\exp(z\Delta_1(\delta,\sigma,x,y,z))\,g(x,y,z,\delta,\sigma)$. Given the expression of Δ_1, the data identifies $\delta\mu(\delta,\sigma,x,y,z)\,\lambda_0(\delta,\sigma,x,y,z)\,\eta(\delta,\sigma,x,y,z)\,g(x,y,z,\delta,\sigma)$. Inverting (x,y,z) to (μ,R,η), this term becomes $\delta\mu\lambda_0(\delta,\sigma,\mu,R,\eta)\,\eta g(\delta,\sigma,\mu,R,\eta)\,J\mathrm{d}\mu\mathrm{d}R\mathrm{d}\eta$ where J is the Jacobian of the transform. Thus, for δ and σ given, $\delta\lambda 0(\mu,R,\eta,\delta,\sigma)h(\mu,R,\eta)$ is identified and so the distribution of (μ,R,η). Besides, using that p -the integral of this term which is also $p(t_t,t_R,t_E)$ - does not depend on δ and that $\delta\lambda 0$ -the differential rate of offer between the treated and the non treated- is increasing with δ **under the assumption that the direct effect δ is always greater on average than the crowding-out effect $\frac{\lambda_0}{\lambda_{00}}$**, we see that for a given σ δ is also identified.

	Freq.	Percent
Gender		
Female	1,162	56.52
Male	894	43.48
# **Gender**		
Child=0	932	45.33
Child=1	501	24.37
Child=2	353	17.17
Child=3+	270	13.13
Marital status		
Single	605	29.43
Divorced	313	15.22
Married	1,138	55.35
Background		
French	1,734	84.34
Western Europe	34	1.65
Rest of Europe	32	1.56
Northern African	207	10.07
Rest of Africa	36	1.75
Other background	13	0.63
Job termination		
Newcomers	209	10.17
End of contract	628	30.54
Resignal	194	9.44
Fired	456	22.18
Other	569	27.68
Education		
Other	398	19.36
BEPC	211	10.26
BEP	467	22.71
BAC equivalent	201	9.78
BAC equivalent	251	12.21
Bachelor equivalent	115	5.59
Bachelor equivalent	183	8.90
Bachelor+	230	11.19
Age		
25	250	12.16
25-30	367	17.85
30-40	674	32.78
40-50	530	25.78
50-55	235	11.43
# obs.	2056	

TAB. 2.1 – Descriptive statistics for cells > 50

2.7.2 Tables

	η	μ	λ_{00}	λ_0	λ_1	Δ_1	$\delta*$	NT	TE
Mean	2.437	0.225	1.659	1.657	1.694	0.209	0.156	-0.002	0.037

TAB. 2.2 – Parameters means

	η	μ	λ_{00}	λ_0	λ_1	Δ_1	$\delta*$	NT	TE
C1	0.003	0.017	0.108	0.107	0.136	0.001	0.002	-0.172	0
C2	0.005	0.032	0.159	0.158	0.184	0.001	0.003	-0.093	0
C5	0.01	0.061	0.25	0.243	0.277	0.001	0.003	-0.028	0
C10	0.024	0.087	0.34	0.337	0.377	0.001	0.003	-0.011	0.001
C25	0.098	0.137	0.629	0.621	0.670	0.014	0.006	-0.002	0.002
C50	1.618	0.190	1.803	1.788	1.842	0.061	0.065	0.000	0.016
C75	2.909	0.257	2.586	2.575	2.635	0.370	0.263	0.000	0.058
C90	3.161	0.347	3.063	3.032	3.115	0.744	0.675	0.000	0.139
C95	3.388	0.428	3.432	3.387	3.475	0.882	1.295	0.000	0.225
C98	3.771	0.570	3.993	3.911	4.028	1.016	2.907	0.000	0.394
C99	4.091	0.721	4.476	4.238	4.438	1.113	5.598	0.000	0.576

TAB. 2.3 – Parameters centiles

	η	μ	λ_{00}	λ_0	λ_1	Δ_1	$\delta*$	NT	TE
Female	-0.285	0.024	-0.128	-0.030	-0.018	0.032	0.057	-0.001	0.016
(ref=Male)	0.033	0.004	0.034	0.048	0.048	0.013	0.010	0.000	0.002
Vocational	-0.618	0.025	0.101	0.303	0.253	-0.077	-0.359	0.013	-0.041
(ref=No diplôme)	0.067	0.008	0.073	0.102	0.102	0.028	0.022	0.001	0.004
Some High School	-0.280	-0.009	0.215	0.368	0.340	-0.051	-0.245	0.011	-0.029
	0.088	0.009	0.096	0.134	0.135	0.037	0.029	0.001	0.005
A-Level	-0.139	0.022	0.316	0.497	0.439	-0.142	-0.399	0.014	-0.057
	0.078	0.009	0.082	0.114	0.115	0.032	0.024	0.001	0.004
Some College	0.302	0.062	0.361	0.412	0.391	-0.026	-0.244	0.010	-0.033
	0.094	0.009	0.111	0.155	0.156	0.043	0.033	0.001	0.006
College	-0.121	0.114	0.551	0.738	0.687	-0.108	-0.403	0.014	-0.055
	0.081	0.009	0.089	0.124	0.125	0.035	0.027	0.001	0.005
Master+	-0.594	-0.005	0.123	0.205	0.154	-0.068	-0.387	0.013	-0.050
	0.075	0.009	0.086	0.120	0.121	0.034	0.026	0.001	0.005
Other	-0.664	0.031	0.314	0.490	0.445	-0.095	-0.346	0.013	-0.043
	0.080	0.008	0.083	0.116	0.117	0.032	0.025	0.001	0.004
25-30	-0.546	-0.002	-0.335	-0.385	-0.395	-0.033	-0.014	0.001	-0.003
(ref=<25)	0.048	0.006	0.051	0.071	0.071	0.020	0.015	0.001	0.003
30-40	-0.203	0.023	-0.432	-0.361	-0.368	-0.028	-0.017	0.001	0.003
	0.047	0.005	0.046	0.064	0.064	0.018	0.014	0.001	0.002
40-50	0.032	0.037	-0.477	-0.320	-0.316	-0.002	0.023	0.001	0.016
	0.056	0.006	0.053	0.074	0.074	0.020	0.016	0.001	0.003
50-55	0.328	0.082	-0.581	-0.534	-0.539	-0.065	0.011	0.000	0.008
	0.075	0.007	0.080	0.112	0.112	0.031	0.024	0.001	0.004
Intercept	2.371	0.122	1.635	1.484	1.547	0.256	0.392	-0.013	0.057
	0.075	0.009	0.085	0.118	0.119	0.033	0.025	0.001	0.005
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES

TAB. 2.4 – Parameters analysis (ALS). TE : Treatment effect. NT : Effect on the Non treated.

Chapitre 3

The equilibrium effects of training

`This chapter is an extract from an article written with Marc Ferracci.`

3.1 Introduction

According to Becker (1964) training increase the unemployed productivity and thus their chance to find a new job. However, the empirical evidence are more elusive as the effect are heterogenous and depends on which part of the process one considers (participation to training, duration in unemployment, duration in the new job). A good sum-up of the literature can be found in Crépon, Ferracci and Fougère (2007b). They recall the four main effects of training on the unemployed, identified since then. First the threat effect, caused by the instant loss undergone by people enrolling in an training session, prevails against the future productivity gain the jobless. Second the lock-in effect -in other words being unable to look for job while in training due to time constraints- is strong and explain why the trained unemployed stay jobless longer than the rest. Third the effects are heterogenous and vary with gender, age, diploma and employment record. Fourth training has a positive effect on the duration of the new job. A recent contribution for the French training system is Crépon, Ferracci and Fougère (2007a) : assuming that the outcomes of the control group are not affected by training, they find significant and negative effects of training on unemployment durations, but also significative and positive effects on employment spells, which is consistent with rest of literature. However, back to Becker's seminal idea, the global labor market conditions are changed. Therefore, the core of this chapter is to replicate this paper without the assumption that the non treated are left unaffected by the policy in order to investigate the equilibrium effects on the unemployed trajectories.

As a matter of fact, on the methodological side, evaluation of active labor market policies (ALMPs hereafter) generally rely on the differences of outcomes between a treatment and a control group. Those differences provide meaningful estimates of average treatment effects under the assumption that individual in the control group are not affect by the policy. This "stable unit treatment assumption" (SUTVA hereafter) is likely to be violated when there are interferences between units of the population under consideration (Rubin, 1990). As SUTVA is generally satisfied in the case of medical experimentation, interactions between workers could lead to its violation in the framework of ALMPs evaluation. A growing literature shows that ALMPs could have very different implications when it is implemented for a large share of the population and when it is implemented on only a small number of participants (Calmfors, 1994, Heckman, Lochner and Taber, 1998, Heckman and Smith, 1998, Davidson and Woodbury, 1993, Blundell, Costa Dias, and Meghir, 2003, Van der Linden, 2005, Albrecht, van den Berg and Vroman, 2005, Lise, Seitz and Smith, 2005). In this paper we evaluate the effects of the training programs that are provided to about 10 percent of the unemployed workers in France. Our paper aims at accounting for equilibrium effects in a model of the labor market with search and matching, inspired from the previous chapter (Cahuc,Crepon,Gurgand,Guitard

(2007)). In this framework, training exerts displacement effects on non trained unemployed workers through three channels. First, trained unemployed workers crowd out those who are not trained because they compete to get the same jobs. Second, by increasing average job duration, training induces employers to create more jobs since they expect to retain workers longer, and to save vacancy costs. Third, training reduces the overall job offers arrival because trained unemployed workers, who are more choosy than those who do not benefit from training, refuse more job offers. This behavior induces employers to open less job vacancies since the probability to meet a workers who refuses job offers is increased when a larger share of the population is trained. It turns out that the first and third displacement effects are negative whereas the second is positive. Accordingly, the sign of the total displacement effect is ambiguous.

We use data from the French unemployment insurance system to estimate this total displacement effect with the help of a mixed proportional hazard duration model to control for both observed and unobserved characteristics. As for most active labor market policies, assignment to training programmes is likely to be endogenous, as it is based on the caseworker's decision and on the worker's agreement. Both decisions depend on observed and unobserved characteristics. As shown by Abbring and Van den Berg (2003), a statistical duration model makes it possible to identify separately the causal effect of training on the subsequent unemployment duration, and the distribution of unobserved characteristics.

Lastly, we use the estimated parameters to simulate the effect of expanding training policies to a larger share of the population. Such simulations are crucial at this moment,as the French Government is considering expanding training policies to a larger share of the unemployed.

The paper is organized as follows : section 2 presents the theoretical model ; section 3 develops the econometric strategy and section 4 describes the data. Results are given in section 5 and section 6 concludes.

3.2 The Model

Let us consider a labor market with a continuum of infinitely-lived risk neutral workers. Time is continuous. Workers can be in six differents states : unemployed and untrained (u_0), unemployed in training (u_1), unemployed and trained (u_2), employed hired untrained (e_0), employed hired while training (e_1), or employed hired after training (e_2). The size of the labor market is constant and normalized to unity, so that : $u_0 + u_1 + u_2 + e_0 + e_1 + e_2 = 1$.

Workers who enter unemployment begin without being trained. Then they enter training at rate μ, and exit from training to open unemployment at rate ε. Since we focus on low skilled workers, we only consider workers who are paid the minimum wage, which is considered as an exogenous variable w. The duration of jobs, denoted by Δ, is match specific. It depends on the adaptability of the worker for the type of job to which he is matched. When an untrained worker and a job are matched, the duration of the job is drawn in an exogenous distribution whose cumulative distribution function is denoted by F, which is assumed to be continously differentiable over its entire support. When a trained worker and a job are matched, the duration of the job is drawn in an distribution which cumulative distribution function is denoted by G. Hence, the distribution of durations of job offers is the same for untrained workers and workers in training, but is different for those who have completed their training spell. The underlying assumption is that workers start to benefit from training only when the training spell is over. This accounts for the fact that training raises the worker's productivity, which allows his/her to draw a job duration in a different - and presumably, higher - distribution.

The assumption that there is a binding minimum wage and heterogeneous job durations allows us to account for two important features of the French labor market for low skilled workers. First, in France, the legal minimum wage covers about 15 percent of the workforce and most low skilled workers are covered by the minimum wage. Moreover, more than 70 percent of workers are recruited with fixed term contracts, this figure being higher for low skilled workers. This feature is related to the specificity of the French labor market regulation with very high firing costs (mainly due to costly legal procedures) for regular contracts with no fixed duration that induce employers to offer fixed term contracts. Therefore, the heterogeneity of low skilled jobs relies much more on differences in contract durations rather than on wage differences.

There is an endogeneous number of jobs. Each job can be either vacant or filled. Filled jobs produce y units of the numeraire good per unit of time, whereas vacant jobs cost h per unit of time. Vacant jobs and unemployed workers are brought together in pairs through an imperfect matching process. The number of contacts between unemployed and firms per unit of time is given by a matching function $M = M(u, v)$ where v denotes the number of vacancies. M is twice continuously differentiable, increasing and concave in both of its arguments, and linearly homogeneous. Linear homogeneity of the matching function allows us to express the probability per unit of time for a vacant job (unemployed worker) to meet an unemployed worker (a vacant job) as a function of the labor market tightness ratio, $\theta = v/u$. A vacant job can meet on average $M(u, v)/v = m(\theta)$ unemployed workers per unit of time, with $m'(\theta) < 0$. The rate at which unemployed job seekers can meet jobs is $\lambda_0 = \theta m(\theta)$. We assume that the probability for a worker to exit unemployment depends on whether he/she is in a training spell or not. This is to allow for a potential *locking-in* effect of training, meaning that workers in training might be more demanding toward job offers they receive. Hence, all job contacts do no necessarily lead to job creation because some job matches may yield jobs with duration that can be considered as too short by the worker. Remind that when a worker enters training he knows that he will be able to draw in a higher distribution of job durations, on condition that he actually finishes his training program.

3.2.1 The worker's decision

Let us denote by V_0, V_1, V_2 the value functions of, respectively, untrained, in training, and trained unemployed workers. Unemployed workers receive unemployment benefits b and enter. $V_e(\Delta)$ denotes the value of a worker recruited on a job of duration Δ. Untrained workers enter training at rate μ. The value function of an untrained worker then satisfies :

$$rV_0 = b + \mu\left(V_1 - V_0\right) + \lambda_0\left(\int_0^{+\infty} \max[V_e(\Delta), V_0]\mathrm{d}F\left(\Delta\right) - V_0\right) \tag{3.1}$$

Workers in training receive job offers at the same rate λ_0 and exit training at rate ε. The associated value function thus satisfies :

$$rV_1 = b + \varepsilon(V_2 - V_1) + \lambda_0\left(\int_0^{+\infty} \max[V_e(\Delta), V_1]\mathrm{d}F\left(\Delta\right) - V_1\right) \tag{3.2}$$

Finally, workers with a completed training spell draw their job duration in distribution G, and their value function satisfies :

$$rV_2 = b + \lambda_0\left(\int_0^{+\infty} \max[V_e(\Delta), V_2]\mathrm{d}G\left(\Delta\right) - V_2\right) \tag{3.3}$$

A job seeker who accepts a job offer with duration Δ is paid w for the duration of the job. At the end of the employment spell, the worker will be unemployed and untrained, as we assume that the benefits of training are lost when the worker reenters open unemployment. Consequently, the value of a job with duration Δ reads :

$$V_e(\Delta) = \int_0^{\Delta} we^{-rt}\mathrm{d}t + e^{-r\Delta}V_0 \tag{3.4}$$

This expression can also be written as follows :

$$V_e(\Delta) = V_0 + \gamma(\Delta)(w - rV_0) \tag{3.5}$$

where $\gamma(\Delta) = \int_0^{\Delta} e^{-rt}\mathrm{d}t = (1 - e^{-\Delta r})/r \geq 0$ is an increasing function of Δ which satisfies $\gamma(0) = 0$. Equation (3.5) implies that untrained workers accept jobs only if $w \geq rV_0$. We assume that this condition is fulfilled. Therefore, the best rule for untrained workers is to accept any job whatever its duration $\Delta \geq 0$. It is now possible to rewrite the value function of an untrained worker defined in equation (3.1) as

$$rV_0 = b + \mu\left(V_1 - V_0\right) + \lambda_0(w - rV_0)\left(\int_0^{+\infty} \gamma(\Delta)\mathrm{d}F\left(\Delta\right)\right) \tag{3.6}$$

Workers in training accept job offers whose duration is above a reservation value denoted Δ_1, which satisfies

$$V_e(\Delta_1) = V_1 \tag{3.7}$$

.

Similarly, trained workers accept job offers whose duration is above a reservation value denoted Δ_2, which satisfies

$$V_e(\Delta_2) = V_2 \tag{3.8}$$

Remind that the difference of exit rates for the untrained/in training workers is not driven by any difference in the job offers arrival rates, but stems from different reservation durations. Thus, entering training affects the value function of any worker only by giving him the opportunity of drawing in a higher distribution of job durations. It follows that V_1 is higher than V_0. Since $V_e(\Delta)$ is a strictly increasing function of Δ with $V_e(0) = V_0$, one gets $\Delta_1 > 0$.

$$rV_1 = b + \varepsilon(V_2 - V_1) + \lambda_0 \left(\int_{\Delta_1}^{+\infty} V_e(\Delta) - V_1 \mathrm{d}F(\Delta) \right) \tag{3.9}$$

$$rV_2 = b + \lambda_0 \left(\int_{\Delta_2}^{+\infty} V_e(\Delta) - V_2 \mathrm{d}G(\Delta) \right) \tag{3.10}$$

From the above system it is possible to write V_0, V_1 and V_2 as functions of the reservation values Δ_1 and Δ_2 and the arrival rate of job offers λ_0.

Hence, the participation conditions (3.7).and (3.8) define a relation between Δ_1 and Δ_2 and λ_0. As it is not possible to analyze the relation between those unknown variables through some comparative statics, we make some calibration exercises in Section (2.3) .

3.2.2 The firm's decision

In this section we describe the job creation behavior of firms. It is assumed that each new match can produce $y > w$ units of good per unit of time for a period Δ. The employer offers a contract that stipulates the duration of the job, Δ, and the wage w. At the end of the period the employer gets rid of the worker. The value of a job with duration Δ, denoted by $\gamma(\Delta)$, satisfies

$$\Pi(\Delta) = \int_0^{\Delta} (y - w)e^{-rt}dt + e^{-r\Delta}\Pi_v \tag{3.11}$$

where Π_v stands for the value of a vacant job. A vacant job costs h per unit of time and meets a worker at rate $m(\theta)$. When a worker is met, he is untrained with probability u_0, in training with probability u_1 and trained with a probability $(1 - u_0 - u_1)$. Accordingly, the value of a vacant job satisfies :

$$\Pi_v = -h + m(\theta)\left(\alpha_0 \int_0^{+\infty} \Pi(\Delta) dF(\Delta) + \alpha_1 \int_{\Delta_1}^{+\infty} \Pi(\Delta) dF(\Delta) + (1-\alpha_0-\alpha_1) \int_{\Delta_2}^{+\infty} \Pi(\Delta) dG(\Delta)\right) \tag{3.12}$$

The free entry condition $\Pi_v = 0$ together with equation (3.11) yields

$$\frac{h}{m(\theta)} = \left(\alpha_0 \int_0^{+\infty} \gamma(\Delta) dF(\Delta) + \alpha_1 \int_{\Delta_1}^{+\infty} \gamma(\Delta) dF(\Delta) + (1-\alpha_0-\alpha_1) \int_{\Delta_2}^{+\infty} \gamma(\Delta) dG(\Delta)\right)(y-w) \tag{3.13}$$

Let us assume that the matching function takes the form $m_0 s^\eta v^{1-\eta}$, $\eta \in (0,1)$, $m_0 > 0$. This implies that $m(\theta) = m_0 \theta^{-\eta}$. Then, from $\lambda_0 = \theta m(\theta)$, we get $m(\theta) = m_0^{1/(1-\eta)} \lambda_0^{-\eta/(1-\eta)} = \Lambda \lambda_0^{-\sigma}$.The free-entry condition (3.13) then writes

$$\frac{h}{(y-w)\Lambda} = \lambda_0^{-\sigma}\left(\alpha_0 \int_0^{+\infty} \gamma(\Delta) dF(\Delta) + \alpha_1 \int_{\Delta_1}^{+\infty} \gamma(\Delta) dF(\Delta) + (1-\alpha_0-\alpha_1) \int_{\Delta_2}^{+\infty} \gamma(\Delta) dG(\Delta)\right) \tag{3.14}$$

We denote by $\Psi_f(.)$ and $\Psi_g(.)$ the probability distribution functions associated to $F(\Delta)$ and $G(\Delta)$. Then we can write the flows of entry and exit between the different states as

$$\begin{aligned}
\dot{u}_0 &= \Psi_f(0)e_0 + \Psi_f(\Delta_1)e_1 + \Psi_g(\Delta_2)e_2 - (\lambda_0+\mu)u_0 && (3.15)\\
\dot{u}_1 &= \mu u_0 - (\lambda_0 \bar{F}(\Delta_1) + \varepsilon)u_1 && (3.16)\\
\dot{u}_2 &= \varepsilon u_1 - \lambda_0 \bar{G}(\Delta_2)u_2 && (3.17)\\
\dot{e}_0 &= \lambda_0 u_0 - \Psi(0)e_0 && (3.18)\\
\dot{e}_1 &= \lambda_0 \bar{F}(\Delta_1)u_1 - \Psi_f(\Delta_1)e_1 && (3.19)\\
\dot{e}_2 &= \lambda_0 \bar{G}(\Delta_2)u_2 - \Psi_g(\Delta_2)e_2 && (3.20)
\end{aligned}$$

At the steady-state equilibrium ($\dot{u}_0 = \dot{u}_1 = \dot{u}_2 = \dot{e}_0 = \dot{e}_1 = \dot{e}_2 = 0$) it is possible to get the values of $\alpha_0 = u_0/(u_0 + u_1 + u_2)$ and $\alpha_1 = u_1/(u_0 + u_1 + u_2)$ as functions of the reservation durations Δ_1 and Δ_2 and the the arrival rate of job offers λ_0.

The equilibrium values of the three unknown variables Δ_1, Δ_2 and λ_0 are defined by the solution of the system of equations (3.14), (3.7).and (3.8). Due to the three dimensions of the system it not possible to solve this equilibrium analytically. In the following section we make some calibration exercises to show the existence of an equilibrium.

From equation (3.14) it is possible to define λ_{00} as the counterfactual equilibrium job offers arrival rate in the absence of the policy ($\mu = 0$), which is merely given by :

$$\frac{h}{(y-w)\Lambda} = \lambda_{00}^{-\sigma} \int_0^{+\infty} \gamma(\Delta) \mathrm{d}F(\Delta) \tag{3.21}$$

3.2.3 A simple calibration exercise

In this section we carry out some simulations to illustrate the labor supply and labor demand relations of our equilibrium model. To make explicit the relations between the three endogeneous variables Δ_1, Δ_2 and λ_0, we calibrate the model with a set of parameters based on some stylized facts of the French labor market, and our data. All parameters are defined on a yearly basis. We set the interest rate r at 0.05. The productivity of a job y is 1.5 whereas the wage w is 1.2. To account for a replacement ratio of about 70% in France we set the unemployment benefits b at 0.8. The cost of a vacancy h is 0.2. The other parameters are calibrate to fit the characteristics of the mean durations in our data : the rate of entry into training μ is 0.2 ; the rate of exit out of training ε is 2 ; the rate of exit out of employment for non trained (resp. trained) workers is $\Psi_f = 0.6$ (resp. $\Psi_g = 0.4$).

r	y	w	b	h	μ	ε	Ψ_f	Ψ_g
0.05	1.5	1.2	0.8	0.2	0.2	2	0.6	0.4

TAB. 3.1 – Calibrated parameters

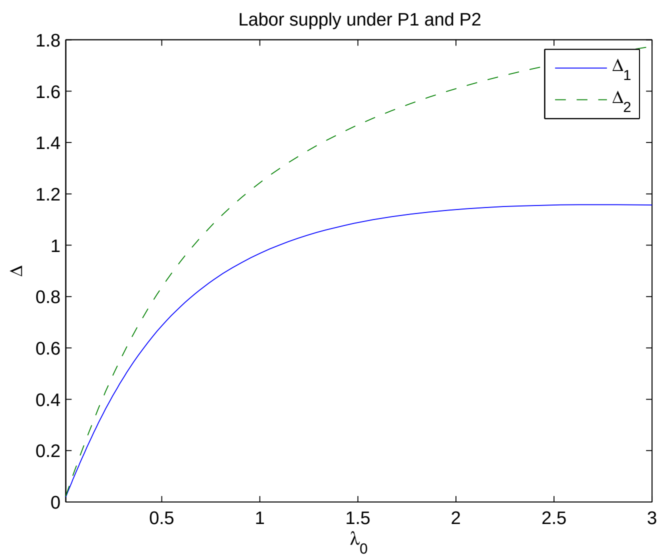

FIG. 3.1 – Labor supply

3.2.3.1 Labor supply

The Figure (3.1) shows the relation between reservation durations Δ_1 and Δ_2 and the arrival rate of job offers λ_0 under the participation conditions (3.7) and (3.8).

An increase in λ_0 raises makes trained people choosier about their job duration, whatever the level of the tension indicator. For jobseekers in training, it raises choosiness only up to some level of λ_0. Hence, during training, the better outside option of the worker is balanced by the fact that training must be finished in order to draw job durations in a higher distribution.

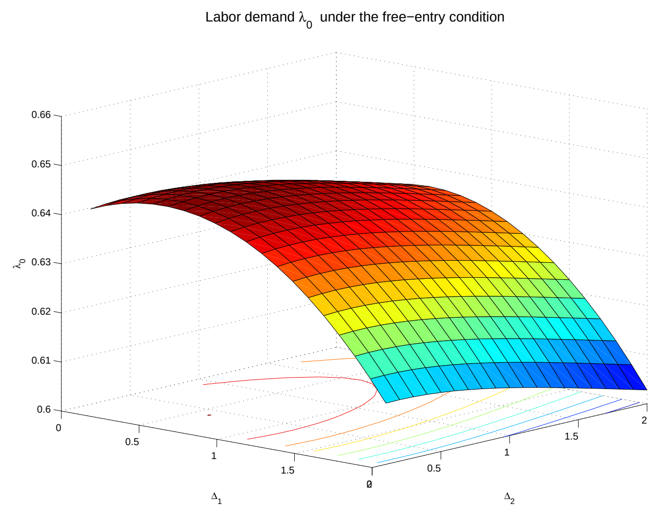

FIG. 3.2 – Labor demand

3.2.3.2 Labor demand

The Figure (3.2) shows the relation between the reservation durations Δ_1 and Δ_2 and λ_0 under the free-entry condition (3.13). λ_0 decreases with Δ_1 and Δ_2, which conveys the fact that firms open less vacancies when jobseekers become choosier in selecting their job duration. The labor market tightness decreases with the reservation duration because employers face a higher probability to meet a worker who refuses job offers of a given duration. It also turns out that the decreasing pattern of the labor demand is more pronounced between Δ_1 and λ_0 than between Δ_2 and λ_0, meaning that vacancy posting is more sensitive to a change in Δ_1 than to a change in Δ_2. Indeed the size of the effect of a change in Δ_1 and Δ_2 on labor demand depends on the stock of workers in training and with completed training, respectively.

3.3 Econometric implementation

Knowledge of all parameters is necessary to evaluate the equilibrium impact of the policy in this model, and the effect of changing the policy intensity. Those parameters can be estimated based on data about : (1) unemployment duration until training, (2) training duration (3) unemployment duration until employment and (4) employment duration. The informal identification argument is as follows. Treatment intensity (μ) can be obtained from the first duration. The second duration contains information on λ_0, and comparing trained and untrained people is informative on the value of λ_1. The distribution of employment durations $F(.)$ and $G(.)$ can be inferred from the third duration and, again, comparing treated and in training individuals is informative on Δ_1 and Δ_2. The discount rate is not estimated, it is set to $r = 0.05$.

This set of parameters can be constrained to fit the labor supply curve defined by equations, (3.7).and (3.8).[1] The labor demand curve, equation (3.2), still depends on two additional unknown parameters, σ and $h/(y-w)\Lambda$. We choose to set $\sigma = 1$. Then, knowledge of the equilibrium point (λ_0, Δ_1) in figure 1 identifies the parameter $h/(y-w)\Lambda$, thus λ_{00}. As there is no information to disentangle h, y, w and Λ, we set $R = h/(y-w)\Lambda$ and estimate R directly. This latter parameter can be interpreted as the inverse of a 'return' to job creation (the profit $(y-w)$ weighted by baseline market efficiency $\Lambda = m_0^{1/(1-\eta)}$, relative to the cost h) : markets with higher R tend to have a lower demand curve.

The cumulative distribution functions of the job durations, $F(\Delta)$ and $G(\Delta)$ are assumed to be parameterized as

$$F(\Delta) = 1 - e^{\Psi_f \Delta} \quad (3.22)$$

$$G(\Delta) = 1 - e^{\Psi_g \Delta} \quad (3.23)$$

We denote the associated probability density functions as

[1] Given r, this is an equality constraint over the parameters.

$$\Psi_f(\Delta) = \Psi_f e^{\Psi_f \Delta} \tag{3.24}$$
$$\Psi_g(\Delta) = \Psi_g e^{\Psi_g \Delta} \tag{3.25}$$

implying that the employment durations have a constant hazard Ψ_i, $i \in (f, g)$.

Notice that duration until training also has constant hasard μ. As a result, λ_0 doesn't have duration dependance either. Including non-stationarity in such an empirical structural model would be a formidable task. As will appear, *observed* duration dependence will be accounted for by unobserved heterogeneity.

In order to account for observed and unobserved heterogeneity, we group data into cells defined by a set of observed characteristics and we assume that, within each cell, unobserved heterogeneity can be captured by a random variable, distributed on a discrete support. We further assume that each group defined by a set of observed characteristics -age,sex, region- *and* a value of unobserved heterogeneity forms a distinct 'job market', over which equations (3.7), (3.8) and (3.14) hold. In this setup, we have to face the usual problem that treatment parameters $(F(\Delta_1), G(\Delta_2)$ and Ψ_f/Ψ_g - the effect of training on the expected duration in employment- can be counfounded with unobserved heterogeneity : a group that is intrinsically more efficient at job search may be also treated less often, so that direct comparison of employment durations accross treated and untreated would, in this example, understate the true policy parameter Ψ_f/Ψ_g. However, it is well known that, in the mixed proportional hazard model, this parameter is non-parametrically identified (Abbring and van den Berg, 2003). Our model differs from this standard setup, but identification is proved in Crépon et al. (2007b). The constant hazards hypothesis plays an important role in this proof, as *observed* duration dependance helps identify unobserved heterogeneity.

The model is estimated separately for cells defined by observed characteristics.

We call t_U total unemployment duration, t_B unemployment duration until entry into treatment, t_T treatment duration and t_E employment duration. In a given market (conditional on X and unobserved heterogenity v), the likelihood has the following expressions (where all parameters, but r and σ, are specific to market (X, v), which is kept implicit for legibility) :

– If the unemployed gets into training before exiting the data :

$$L(t_U, t_B, t_T, t_E|X, v) = \mu(v)e^{-(\lambda_0(v)+\mu(v))t_B}\lambda(v)^{1-c_T}e^{-(\lambda_1(v)+\epsilon(v))t_T}\psi_f(v)(1-c_E)e^{-\psi_f(t_E-\Delta_1)}$$

– If the unemployed does not get into training before exiting the data :

$$L(t_U, t_B, t_T, t_E|X, v) = \lambda_0(v)^{1-c_U}e^{-(\lambda_0(v)+\mu(v))t_U}\left(\psi_f(v)^{(1-c_E)}e^{-\psi_f(v)t_E}\right)^{(1-c_U)}$$

where $c(U) = 0$ when the unemployment spell is censored and 1 otherwise, $c(T) = 0$ when the training spell is censored and 1 otherwise and $c(E) = 0$ when the employment spell is censored and 1 otherwise. We also impose the three restrictions derived from equations (3.7), (3.8) and (3.14), which implicitly define the three endogenous variables within each market :

$$\lambda_0\left(\Psi_f/\Psi_g, \sigma, \mu, R, \eta\right)$$
$$\Delta_1\left(\Psi_f/\Psi_g, \sigma, \mu, R, \eta\right)$$
$$\Delta_2\left(\Psi_f/\Psi_g, \sigma, \mu, R, \eta\right)$$

The observable likelihood then has the following expression :

$$L(t_U, t_B, t_T, t_E|X) = \int L(t_U, t_B, t_T, t_E|X, v)dH(v; \pi)$$

where $H(v; \pi)$ is the distribution of unobserved heterogeneity and π its parameters. Heterogeneity applies to μ, R and η and is specified with two factor loadings :

conditional on X they have values

$$\mu = \exp(\pi_\mu^1), R = \exp(\pi_R^1), \eta = \exp(\pi_\eta^1)$$

with probability p and values

$$\mu = \exp(\pi_\mu^2), R = \exp(\pi_R^2), \eta = \exp(\pi_\eta^2)$$

with probability $1-p$. This specification ensures that μ, R and η can be correlated in an unconstrained manner. For instance, unobserved features can make treatment μ more intensive in markets that have longer contracts (η).

For tractability reason we split our sample into cells over which estimations are run separately. As explained above a cells is a set of spells sharing the same age, sex and living in the same region. A 'market' will be the set of spells sharing the same observed characteristic quoted above and the same unobserved type. Thus there are two 'markets' in each cell. We estimate the maximum likelihood above as a constrained parametric duration model with finite mixture using the software KNITRO AMPL. This estimation provides us with a set of parameters by unobserved types : in other words we end up with an estimate by 'market'. Then we work out MLE variance through MATLAB.
As the likelihood is not differentiable in Δ_1, and Δ_2 we smooth it by replacing the dummy functions $t_E - \Delta_i > 0$ (i=1,2) with logistic functions $\frac{1}{1+exp(-6*(t_E-\Delta_i))}$ The estimation lasts 5 nearly days. A few cells (less than 5) shows convergence issues.

The distribution of parameters over all markets can then be presented non-parametrically. In order to have a more structured view of the results, we can also project the parameters linearly over the observed characteristics (namely age, sex and region), so as to describe the effects of observable characteristics on the various durations.

Based on the estimates, we can then compute a set of evaluation parameters and counterfactuals. In each case, there are as many effects as there are markets. In this sense, our specification is very flexible with respect to heterogeneity of treatment effects. The main effects we are interested in are the following :

- The direct effect of the treatment : the net exit rates from unemployment of workers in training ($\lambda_0\bar{F}(\Delta_1)$) and trained workers ($\lambda_0\bar{G}(\Delta_2)$), compared with the exit rate λ_0 of the non treated. This estimates can be compared with the SUTVA if no equilibrium effect.
- The effect of the policy on the non-treated : the exit rate from unemployment for the non treated λ_0 compared with the exit rate λ_{00} that would prevail if the policy did not exist ($\mu = 0$). This is a measure of the policy crowding-out on the untreated.
- The equilibrium effect of the treatment on the treated : $\lambda_0\bar{F}(\Delta_1)$ and $\lambda_0\bar{G}(\Delta_2)$ compared with the exit rate λ_{00} in the absence of the policy.

3.4 Application to training policies in France

3.4.1 Institutional framework

In this section we describe briefly the general organisation of the French training system for jobseekers (FTSJ hereafter), as well as the process by which unemployed persons enter training programs.

General organization. The FTSJ is rather complex, as it is run by three different players : the State, the administrative regions and the social partners (trade unions and employers' organizations). In the FTSJ, a major distinction should be made between the jobseekers eligible to unemployment insurance (UI) benefits, and the others. The State plays a key role, as it funds training programmes for the long-term unemployed who have exhausted their rights to UI, as well as for welfare recipients. It also provides revenues to jobseekers who are not eligible to UI and who get through State-appointed training programmes. Besides, the State offers training both to the eligible and non-eligible unemployed through the public employment service, *Agence Nationale pour l'Emploi* (ANPE hereafter), which role is to counsel the unemployed for their search activities and to monitor them. This role was reinforced in 2001 in the framework of the PARE ("*Plan d'Aide au Retour à l'Emploi*") reform. Since this reform, the local ANPE agencies are the obliged spot for any jobseeker willing to enter a public training programme.

In France the social partners manage the institution in charge of the payment of UI benefits, called "*Union nationale interprofessionnelle pour l'emploi dans l'industrie et le commerce"* (UNEDIC hereafter). Before 2001, the role of UNEDIC was to provide the UI recipients who got trained with a benefit which was constant over time, contrary to the decreasing UI benefits then granted to regular UI recipients. Since the PARE reform set up in 2001, UNEDIC now funds integrally the benefits of those trainees eligible to UI. Besides, UNEDIC and its local agencies, called "*Association pour l'emploi dans l'industrie et le commerce*" (ASSEDIC hereafter), are now in charge of prescribing and buying some specific training courses for the eligible jobseekers. The table below proposes a reminder of the acronyms associated to the general organization of the FTSJ.

Reminder - the French training system

ANPE	-	*Agence National Pour l'Emploi* Public employment service, counsels and monitors unemployed workers. Run by the state.
ASSEDIC	-	*Association pour l'Emploi dans l'Industrie et le Commerce* Local agencies of the UNEDIC.
BMO	-	*enquête Besoin de Main d'Œuvre* Survey conducted by the ASSEDIC every year since 2001. Collects firms' job opening predictions for the next year. Helps ANPE assign training programs.
FNA	-	*Fichier National des ASSEDIC* National register of unemployed workers.
FTSJ	-	*French Training System for Job seekers*
PARE	-	*Plan d'Aide au Retour à l'Emploi* Reform introduced in Autumn 2001. Reinforcement of the counseling services provided by the ANPE. Compulsory meeting with an ANPE caseworker every six months.
UNEDIC	-	*Union Nationale interprofessionnelle pour l'Emploi Dans l'Industrie et le Commerce* Institution in charge of paying unemployment benefits. Run by the social partners (unions and employers). Pays unemployment and welfare benefits. (Since 2001) prescribes and buys some specific training courses. Conducts a yearly survey on local labor demand (BMO). These tasks are run at the local level by the ASSEDIC agencies.

Finally, the administrative regions are also in charge of the funding of training programs. Moreover, they express their needs for skills at the local level to ASSEDIC and ANPE agencies, based on the vacancies that are open every year. The ANPE agencies are then asked by legislation to assign jobseekers to training programs suited to the vacancies. For their part, ASSEDIC agencies are in charge of the same kind of assignment for eligible jobseekers, but on the training programs they fund. In other terms, training capacities are -presumably- calibrated to fit the nature of open vacancies.

Assignment process. Entry into training programs may result from a proposal by ANPE caseworkers or from the jobseeker's own initiative, although we do not have this information in our data. Regarding the ANPE proposals, it should be noted that the PARE reform introduced in 2001 consisted in significantly stronger individual counseling services offered to the unemployed (whether insured or not). Since then, a meeting with an ANPE caseworker (typically 30 minutes long) is now compulsory for all newly registered unemployed and recurs at least every 6 months. Depending on the person's profile, the caseworker can schedule follow-up interviews between two compulsory meetings, and interviews can be requested at any moment by the unemployed workers themselves. Apart from a wide range of counseling measures, training programs may be proposed to jobseekers during these interviews. In theory, the latter are free to accept or refuse any program they are proposed. Theoretically, a refusal can lead to a cut in unemployment benefits for eligible jobseekers. In practice, however, sanctions for refusing a training program are almost never taken.

As is described in the the next section, the ASSEDIC conduct a yearly survey on the predicted vacancies at the local level. In particular, this survey intends to give some information to the ANPE caseworkers to help them assign the unemployed to training programs fitted to the open vacancies. In this framework, it is most likely that the need for skills at the local level is correlated to the probability of being treated on a specific market. Another consequence is that caseworkers propose training programs that are generally oriented toward the acquisition of specific human capital. In theory, the less employable persons have priority access to training programs. Yet, some recent field studies (see e.g. Dares, 2006) show that low-skilled workers are less likely to accept training, although they are more likely to be proposed such programs by caseworkers. This suggests that self-selection plays a significant part in training participation.

On the other hand, jobseekers may find training programs by themselves. Some surveys indicate that those programs are generally oriented toward the acquisition of more general human capital, although we do not observe the contents of training in our data. In that case the unemployed can benefit from some public funding[2] to cover the program's tuition costs. However, this requires that the program be validated by an ANPE caseworker, who is in charge of checking that the program is somehow useful, with respect to the jobseekers professional project, as well as to the needs of the local labor market. The above mentioned study by Dares (2006) also shows that low-skilled workers are far less likely to ask for the validation of a training program than, for instance, executives. Finally, it turns out that ANPE caseworkers have much power in the assignement process, as they may eather prescribe or validate the training programs.

3.4.2 Data description

Our empirical analysis makes use of data extracted from the "*Fichier National des Assedic*" (FNA hereafter) collected by UNEDIC. The FNA file contains information on all the workers entering unemplyment and who are either UI or welfare recipients. This is due to the fact that UNEDIC is in charge of paying UI and welfare

[2]The funding may come from the administrative regions, the State or UNEDIC, depending on the eligibility of the jobseeker, and on the contents of the program.

benefits.

Our data set covers the 2001-2005 period. A strong reason for considering this period only is that between 1993 and 2001, the time profile of UI benefits was decreasing over the unemployment period (it is constant since the 2001 reform). However, for those unemployed workers who entered a training programme between 1993 and 2001, the UI benefits remained constant until the programme stopped. Hence, the system was providing an incentive to enter a programme, whatever the quality of the latter. By reintroducing a constant benefit over the whole period of eligibility to UI, the PARE reform removed this feature. For this reason, we focus in this paper on the analysis of unemployment spells beginning between 2001 and 2005.

The sample has been drawn randomly from the FNA file. More precisely, our sample is made of one unemployed out of forty entered into the FNA file between July 2001 and December 2005. For each individual, the extracted file contains precise information on all the unemployment spells that could have occurred since 1993. The sample mixes information collected by UNEDIC, which is in charge of paying the unemployed their benefits, and by the ANPE (i.e. the public employment service), which role is to counsel the unemployed for their search activities and to monitor them. It contains the dates at which workers are registered and deregistered as unemployed by the public employment service, as well as the start and termination dates of UI eligibility periods. Information about the nature of the benefits makes it possible to identify training spells from regular unemployment spells. The sample we use includes 270,139 spells, among which 19,673 spells are associated with at least one training period.

Definition of spells. Entry into and exit from unemployment are recorded on a daily basis, so that we model duration in continuous time. In our evaluation, we consider training partly as a separate state. This means that we model explicitly transitions from unemployment to training and from training back to unemployment, but we assume that the duration of the current unemployment spell is augmented by the time spent in all training spells that occur during this unemployment spell. This allows us to examine directly the impact of the previous occurrence of a training programme on the transition rate from unemployment to employment, whatever the time already spent in the current unemployment spell. In other words, any observed unemployed spell starts with a transition from employment to unemployment and it ends with the first subsequent transition to employment (it is right-censored if no transition to employment is observed).

Hence, in our modeling, transitions may occur from unemployment to employment, from unemployment to training, from training to employment and from employment to unemployment. We do not consider transitions from employment to training, as people must stay at least a few days unemployed before getting into a training programme offered to unemployed workers. An employment spell starts with a transition from unemployment to employment. The duration of an employment spell is complete when the individual reenters unemployment. In our data people that have completed a training spell are automatically registered in open unemployment at the end of this spell. This is the case even if they exit to employment at the very end of the training spell. In the framework of our theoretical model, this feature makes it possible to distinguish between workers who have actually completed their training spell, and those who have not, and thus identify the reservation parameters Δ_1 and Δ_2.

3.4.3 Results

We estimate the emprirical model under the participation conditions (3.7) and (3.8) and under the free entry condition (3.14). The estimated parameters allow to simulate the impact of training on aggregated labor market outcomes. We define cells by age, sex and region. Each cell is assumed to represent a separated labor market where the parameters are independently estimated. We first present the estimated parameters. Then, we evaluate the impact of training on transitions between unemployment and employment. Finally, we analyze the effect of training on unemployment.

3.4.3.1 Estimated parameters

Parameters are independently estimated on cells assumed to represent separated labor markets differentiated by sex, age, education, marital status and nationality. We end up with 788 cells. The largest cell contains 498 observations. We give a few descriptive statistics on the cells in Table (3.2) and Table (3.3).

Table (3.4) gives the means of the following parameters, weighted by the size of each cell : the rate of entry into traing μ; the rate of exit out of training ε; the rates of exit out unemployment λ_0, $\lambda_0\bar{F}(\Delta_1)$, and $\lambda_0\bar{G}(\Delta_2)$; the rates of exit out of employment ψ_f and ψ_g; the reservation durations Δ_1 and Δ_2 and the value of the counterfactual arrival rate of job offers λ_{00} in the absence of training. Table 3 gives the centile distribution of those parameters.

The results show that training affects unemployment durations. Without taking equilibrium effects into account the impact of the treatment on the rate of exit out of unemployment of treated individuals is simply defined as the ratio $\lambda_0\bar{F}(\Delta_1)/\lambda_0 = \bar{F}(\Delta_1)$ (resp. $\bar{G}(\Delta_2)$) for workers in training (resp. workers with completed training). The average unemployment duration of untrained workers is 0.39 year, while the average duration of trained workers is 0.54 year. This difference comes from the fact that workers having completed training refuse more job offers because they can draw job durations in a higher distribution. This result is often in the empirical literature as a "locking-in" effect of training, implying that training reduces the job

		#	%
Sex	Male	391	50
	Female	397	50
Motive	1	193	24
	2	354	45
	3	241	31
Age	<25	222	28
	25-30	215	27
	30-40	191	24
	40-50	160	20
N. OBS		788	

TAB. 3.2 – Cells descriptive statistics

Treatment Rate	Mean	0.064
	Min (>0)	0.002
	Max	0.5

TAB. 3.3 – Treatment rate among cells

	μ	ε	λ_0	$\lambda_0\bar{F}(\Delta_1)$	$\lambda_0\bar{G}(\Delta_2)$	λ_{00} (simulated)	ψ_f/ψ_g	Δ_1	Δ_2
Mean	0.253	3.125	2.517	1.516	1.836	1.930	1.406	0.31	0.32

TAB. 3.4 – Means of estimated parameters

	μ	ε	λ_0	$\lambda_0\bar{F}(\Delta_1)$	$\lambda_0\bar{G}(\Delta_2)$	λ_{00}	ψ_f	ψ_g	Δ_1	Δ_2
C10	0.003	0.391	0.177	0.053	0.175	0.000	0.049	0.060	0.001	0.001
C25	0.030	3.877	0.377	0.306	0.345	0.009	0.207	0.214	0.004	0.002
C50	0.104	18.752	1.017	0.700	0.760	0.490	1.613	1.049	0.013	0.010
C75	0.877	204.549	12.322	6.769	8.310	6.135	7.489	4.601	0.120	0.147
C90	2.830	822.480	53.077	37.815	45.265	15.608	23.838	15.009	0.500	1.129

TAB. 3.5 – Centiles of estimated parameters

seeker's search effort. Note that in our theoretical model this "locking-in" effect only stems from an increase choosiness on the part of trained workers.

The behavior of workers in training is close to the one of the trained workers, with reservation durations Δ_1 and Δ_2 equal respectively to 0.31 and 0.32. The values of Δ_1 and Δ_2 mean that on average, treated workers refuse short-term contracts of about four months, whereas non treated job seekers accept any contract they are proposed.

Besides, the mean value of the ratio ψ_f/ψ_g indicates that the average employment duration of people with completed training is about 40% higher than the average duration of non treated people, as well as workers that did not complete their training spell. This result is close to those found by Crépon, Ferracci and Fougère (2007), who estimate a duration model to evaluate the effects of training without making any structural assumptions. Training is found to increase employment durations, suggesting that it could raise the productivity of the matches between workers and jobs. Accordingly, if jobs are subject to exogeneous productivity shocks that affect the job destruction behaviour of firms, trained workers will experience longer job durations.

However this approach does not take into account the fact that training may change the value of the arrival rate of job offers for non treated workers. The value of the counterfactual exit rate of unemployment λ_{00} allows to identify this equilibrium effect of training. Remind that in the absence of policy the exit rate out of unemployment only depend on the arrival rate job offers. A striking result is that the average unemployment duration of all job seekers in the absence of the policy, $1/\lambda_{00}$ is 30 % higher than the estimated unemployment duration of non treated people, $1/\lambda_0$. This is the result of the positive effect of training on employment duration. In the framework of our model, training make firms save the vacancy costs associated to short-term contract durations. Firms react to this increase by posting more vacancies, which benefits to both treated and non treated people.

Table 3.6 documents the relation between the estimated parameters and the features of labor markets. We see that women tend to enter more into training, but they also exit training more quickly (ε is higher for women than for men). The impact of training on the transition rate out of unemployment is also higher for women than for men . Even if the training is more profitable for women -as the effect of training on employment duration ψ_f/ψ_g is relatively higher for them- they are less choosy too : the reservation durations are smaller for them and consequently the lock-in effect relatively smaller. The youth -below 25- enter more than their elderly. They exit more quickly too. But unlike women the training seems less profitable profitable than for the rest of the sample.

3.4.3.2 Simulation of policy effects

The benchmark results of the previous section indicate that evaluating training without without accounting for equilibrium effects can yield false estimates of the effect of the treatment. This suggest that the SUTVA is not necessarily verified in the context of training policies, a result already found by Ferracci, Jolivet and Van den Berg (2008). In this section we simulate the impact of expanding training to a larger share of the population.

	$\hat{\mu}$	$\hat{\epsilon}$	$\hat{\lambda}_0$	$\hat{\lambda}_0\bar{\bar{F}}(\hat{\Delta}_1)$	$\hat{\lambda}_0\bar{\bar{G}}(\hat{\Delta}_2)$	$\frac{\hat{\psi}_g}{\psi_f}$	$\hat{\Delta}_1$	$\hat{\Delta}_2$
Female	0,058	12,067	0,279	0,405	0,423	0,347	0.001<	-0,008
	0,001	0,259	0,015	0,008	0,01	0,006	0,009	0,001
25-30y	-0,058	-18,454	-0,733	-0,583	-0,655	0,034	0.001<	0.001
(ref= <25)	0,001	0,322	0,018	0,01	0,013	0,01	0,012	0.001
30-40y	-0,07	-26,228	-0,617	-0,56	-0,46	0,116	0	-0,005
	0,002	0,354	0,02	0,011	0,015	0,003	0,013	0,001
50-40y	-0,097	-31,518	0,244	-0,247	0,101	-0,305	0.001<	0,019
	0,002	0,414	0,025	0,014	0,018	0,005	0,014	0,001
Motive 1	-0,156	-22,41	-2,464	-1,105	-1,672	-0,063	0,001	0,047
	0,003	0,894	0,039	0,023	0,028	0,027	0,025	0,002
Motive 2	-0,131	-16,17	-2,154	-1,079	-1,507	0,209	0,001	0,059
	0,003	0,903	0,04	0,023	0,029	0,025	0,026	0,002
Intercept	0,391	78,311	5,401	2,703	3,488	1,202	0,001	0,877
	0,004	1,013	0,048	0,027	0,034	0,066	0,031	0,002
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES

Tab. 3.6 – Parameters analysis (OLS)

3.4.4 Conclusion

This paper shows that equilibrium effects of training matter : the demand effect exceeds the crowding-out effect. Training increases the expected duration in employment and thus reduces vacancy costs : employers are incented to create more jobs. This effect is higher than the crowding out or the queue effect : the created jobs are available for anybody, trained or not. The model also accounts for the strong lock-in effect observed while the unemployed are in training. The gains of employability are high enough to make the training drop-out very costly. People prefer to stay in training unless they get a very long job offer. Equilibrium effects tend to alter the direct effect of the training that is the change in the expected employment duration, as they generate a duration reservation and they have an impact on the job arrival rate. By neglecting them, one overestimate the impact of training the employment duration and thus its effect on job arrivals. Many questions stay unanswered at this stage : the identification the robustness of the result to the cell-division, the stability of the algorithm, the stock effect. Yet it seems already worthy to account for the equilibrium effect even if a small share of the population is treated.

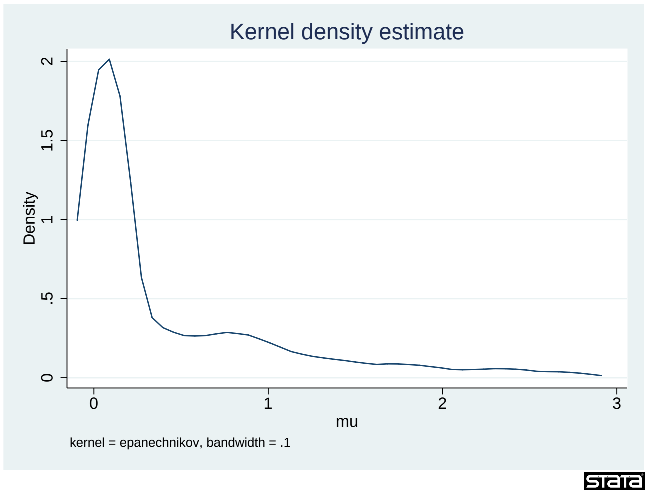

FIG. 3.3 – Density of the rate of entry into training μ

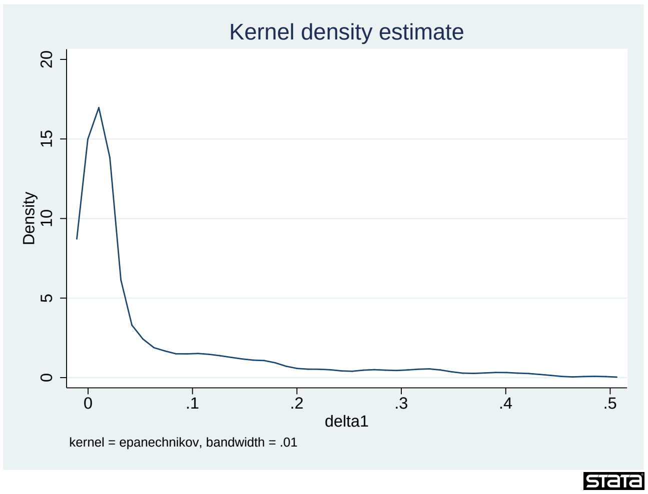

FIG. 3.4 – Density of reservation duration Δ_1

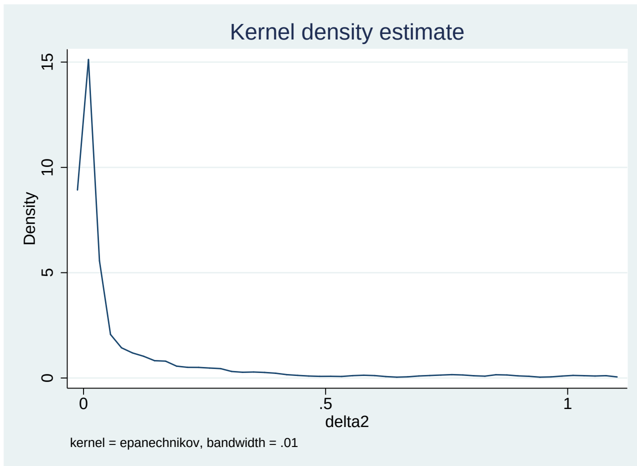

FIG. 3.5 – Density of reservation duration Δ_2

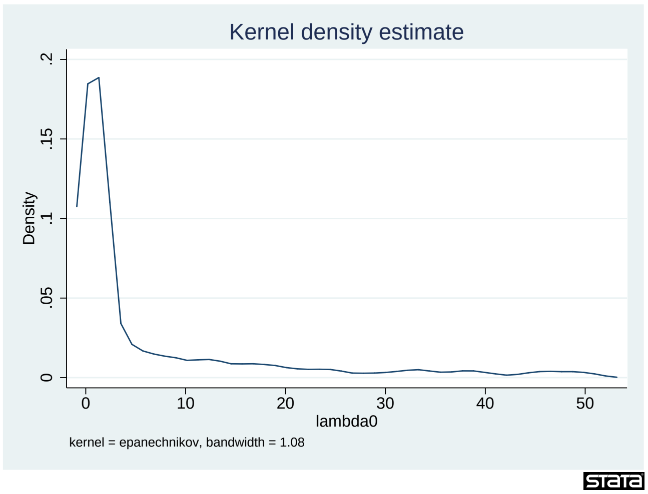

FIG. 3.6 – Density of the exit rate out of unemployment for non trained workers λ_0

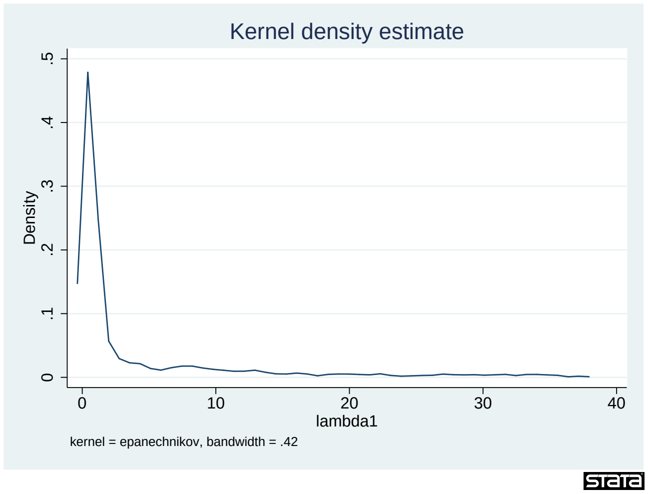

FIG. 3.7 – Density of the exit rate out of unemployment for workers in training $\lambda_0 \bar{F}(\Delta_1)$

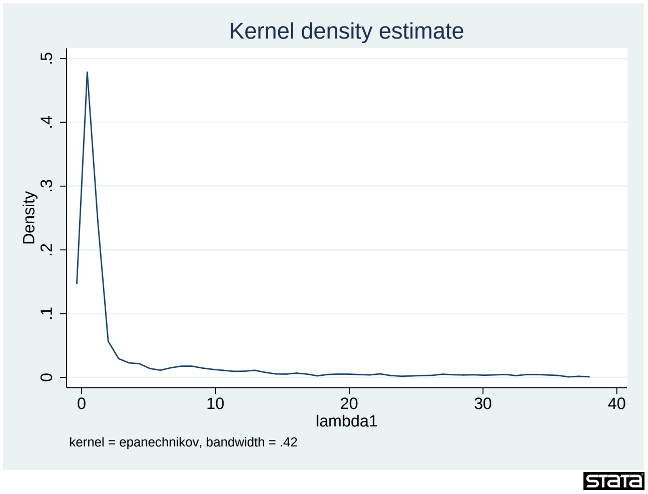

FIG. 3.8 – Density of the exit rate out of unemployment for trained workers$\lambda_0 \bar{F}(\Delta_2)$

Chapitre 4

Who goes from unemployment to self-employment ? Evidence from the GSOEP

4.1 Introduction

The issue of entrepreneurship is a crucial one. By sustaining both innovation and employment, the independent stand at the core of the economy. Classical macroeconomic articles such as Romer (1990) and Aghion et al. (1992) emphasize business creators as source of innovation and growth . Taking a microeconomic point of view, this paper assesses the effect of entrepreneurship on employment. Indeed, the idea -that institutional intervention towards the self-employed may help reduce unemployment- seems to be in fashion among European politicians. On the ground, interventions in favor of entrepreneurs are of various kinds : completing imperfect information by advertising existing opportunities, correcting market failures by alleviating legal and credit constrains on business creators and investing in human capital by supporting education that make business creation easier. For the applied economist preparing and evaluating these policies become a matter of concern and require a deep understanding of the career of the self-employed. In order to address credit constraints Germany launched a series of measures easing the allowance condition for the unemployed in 1994. The result as been deemed as disappointing by Pfeiffer et al. (2000) in term of long-term job creation : it mostly select people who would have tried entrepreneurship anyway while it does not increase their survival chances in business. Alternatively, education may develop entrepreneurial talents and opportunities in the long run and thus could be a key element of future policies supporting self-employment. More precisely, in the German context where vocational education has been stressed for decades as a key to integration on the job market, the interaction of unemployment, self-employment and education is of special interest. Therefore the aim of this paper is to identify the effect of education on business entry for the jobless as well as the duration of their ventures. Besides comparing this effect with other human capital channels such as family background and job experience is a way to assess whether policies favoring education can effectively enhance social mobility or not.

Until recently, the literature had frequently addressed the issue of business entry and the credit constraints that may occur thereof. Evans et al. (1989) builds a static model of selection into entrepreneurship under credit constraints before finding out empirically on 1443 individuals of the National Longitudinal Survey that assets owned do increase the probability to get self-employed over 1976-1978 period after controlling for education and work experience. Because assets detained by households may be endogenous, Blanchflower et al. (1998) uses received gifts and inheritances instead, but still confirms the impact of credit constraints on the would-be entrepreneurs with the National Child Development Study 1981. By the way it appears that entrepreneur's sons and former apprentices are more likely to jump into self-employment. Nonetheless the author fails to show any significant impact of psychological factors such as risk aversion. The issue of credit constraints comes out again with Hurst et al. (2004) who show using inheritance and real estate gains that wealth effect on the yearly business entry is sheerly convex over the 1989-1994 period. Some natural experiments have also been exploited to deal with wealth endogeneity : see for instance Banerjee et al.(2002).

Even if the jobless who get independent differ beforehand by their motivation, ability and need of public support, few of these papers comes across the relationship between unemployment and self-employment. Leighton et al. (1989) exploit the National Survey of Young Men and find that lower-paid wage workers, unemployed or unstable workers are more likely to become self-employed at some point of their careers. As said above, Pfeiffer et al. (2000) assess the 1994 measure in Germany. However some questions remain unanswered. It is not known for instance in which extent entrepreneurship is used to disguise unemployment and escape the stigma the latter may cause.

More generally, despite its importance, little has been done the career of the individuals after they get self-employed. The case for this selective interest may be in accordance with the conventional wisdom that assumes market efficiency to be the foremost concern of economists : from this point of view, the only reason that may entitle the regulator to intervene is a possible failure of the credit market that could prevent talented individuals from taking up a profitable activity. By contrast what happens afterwards to the newly self-employed seems to be let to market forces. Once the market credit amended the better projects are supposed to success while the others are doomed to fail. This rationale may account for the lack of papers regarding the fate of freshly created business among household surveys. Our guess is that this bias in interest is also data-driven. Recording an entry into business is often a delicate task in household surveys. Tracking entrepreneurs through their business life is even harder. Hamilton (2000) uses an alternative to the PSID -the Survey of Income and Program Participation- and finds that some people go self-employed in spite of lesser income than their employed counterparts. Taylor (1999) focuses on self-employed duration and termination on the British Household Panel Survey. It turns out that nearly 40% of the freshly created business started since 1991 have not survived their first year. According to his results the fittest are those with previous work experiment but no previous unemployment. Besides, the wealthier when the venture starts, the better.

The aim of my research is to discuss whether driving the unemployed towards entrepreneurship is a plausible remedy to unemployment and how human capital can help. In other words, I look to identify how much education can move the line of job mobility in a world where social continuity and family tradition are deemed to be strong. I make use of the German Socio-Economic Panel (GSOEP) which provides a comprehensive view of the career of the German workforce since 1984. Taking advantage of the longitudinal structure I am able to describe not only what can drive the jobless towards entrepreneurship but also how the businesses of the same individuals evolve then. I can thus disentangle the effect of human capital under various forms : father's job status, nationality, geography and education -vocational or academic-. I model job status each year as a semi-markovian process. I start with simple probit reduced-form estimates. I rely then on alternative strategies such as random effects model to address unobserved heterogeneity issue. As I do not have robust measure of wealth either, I cannot extend my analysis to financial capital.

The paper proceeds as follows. First I introduce the background and the data in section 4.2. I recall the relevant features of the German Socio-Economic Panel (GSOEP henceforth), describe the variables and the sample of interest. In section 4.3.1 I give statistics concerning entrepreneurs in Germany ranging from macroeconomic and cross-section evidence to duration and job status transition data. Then I estimate transition models from employment and unemployment onto business as well as the probability to stay in self-employment (Section 4.5). I use classical control variables : background, father status, education, previous experience. Beside the usual exogeneity issue, I am also concerned by left-censoring of the variables tracking experience in unemployment or entrepreneurship. Therefore I carry out several estimations where I successively control for pre-survey biography when available or hidden heterogeneity (random effects). I eventually get robust estimates of the covariates effects.

4.2 Background and data

The first paragraph of this section recalls the common definition of 'self-employed' in Germany, a few institutional changes that happened to entrepreneurship over the past few years as well as the allowance reform of 1994. The second paragraph describes the data.

4.2.1 Institutional context

The legal and common definition of self-employment in Germany is stable over the period. Formally all the self-employed have to pay for their own social security. Although false claims by employers wishing not pay for their employees' social security are possible, the DIW thinks that such behaviours are unlikely. The self-employed are usually divided into three broad groups : the farmers, the free-lances and the rest . Free-lances work in services -IT,law,insurance- while the rest -labeled as 'Other' in the panel- take up more traditional businesses as craftsmen, shopkeepers or manufactured goods producer.

Despite the stability of the concept as whole, some changes have occurred regarding the definition of the categories of entrepreneur. When the GSOEP was launched, the latter had to get through apprenticeship and to pass a degree called *'Meisterschaft'* after a few years of experience. It changed gradually over the past few years such that a *'Meisterschaft'* is no longer compulsory in most professionstoday . On the other hand the free-lances are made of academic -virtually free of regulation- and 'Freie Berufe' which are highly regulated (like architect, insurer...). Because of the ambiguous definition more and more self-employed considers themselves as free-lances in the recent period of the panel. It happens for instance that some individual start a spell of self-employment as 'Other' and end it as free-lances. In other words the partition in farmers, free-lances and goods producers may is to be interpreted cautiously. At a further stage, I could use a very precise job classification (1000+) also available in the GSOEP. Indeed, at such a level of accuracy, the changes described above are discontinuous and may be exploited as instrument to identify the effect of a diploma such as the *'Meisterschaft'*.

In 1994 the government launches a measure called "Bridging the allowance" that aimed at supporting -financially- the jobless starting up their businesses. An evaluation of this reform is available in Pfeiffer et al. (2000) . I do not redo the job here. Instead I control for time discontinuity at the time of the reform. Consistently, I do not find any clear-cut impact of the reform on my data.

4.2.2 Data

The GSOEP is a nationwide longitudinal survey of households living in Germany conducted by the German Institute for Economic Research (DIW) based in Berlin. It manages to conciliate item consistency over time with the major changes experienced by the German society over the last two decades. More specifically, it mirrors the institutional features of entrepreneurship. Started in 1984, it includes nowadays more than 22000 people belonging to nearly 12000 households. East German and Immigrants have joined the West German original core during the various sample refreshments carried out since 1984. One has access to numerous cross-section variables at household and individual levels, from the educational attainment to job and marital status or nationality and geographical location . Various income and asset data are also collected. To track the self-employed, one relies mostly on job status variables -defined year by year from the `stib****` variables of the GSOEP - that break down the adults[1] into 8 categories : the pensioners, people out of the work force, the students, apprentices, the jobless, the employees, the civil-servants and the self-employed. The respondent must defined herself as one of these. It is also known whether a self-employed is a farmer, a free-lance or else.

Three issues -all related to measurement errors- must dealt with. First, the categories are arbitrary or ambiguous sometimes. The weak definition of the free-lances -as quoted above- is just one example. The exact difference between unemployed and people out of the workforce is subject to discussion. The case of people doing a *'Meisterschaft'* is ambiguous : if complying with the GSOEP direction, they must be declared employees, but some of them have been seemingly declared students or apprentices. Second, the types of transition one can record are restricted. Although the job status variable can be used to track the career of individuals, they

[1] People above 16.

do not suffice to catch every change. For instance an individual changing of job but remaining employee will not appear as changing since her status does not change. In other words finer transitions would claim more variables than the `stib****` to be recorded. Some of these variables are available -those relating intra-employment transition for instance - others -like causes for quitting self-employment- are not[2]. The third issue is the frequency of the survey. The update of the job status variables is made yearly. This periodicity may suit self-employment spells but seems too coarse to track unemployment : usually labor economists have daily or weekly data for duration in unemployment.

Eventually all the male residents[3] surveyed at least once between 1984 and 2003 and whose age ranges between 16 and 55 at the time they entered the survey are selected in my master sample. Thus I get a wide un-balanced file recording 16678 individuals. Out of them,1984 got self-employed at some point of the survey. They represent $13,9\%$ of the population of interest. In other words there are enough of them to in the master sample to make a valid statistical analysis. Each observation is sample-weighted according to the recommendations of the DIW. As usual, one can build a long file from the latter wide file. There are 118506 valid observations in this long-file, each of them indexed by individuals and year. If one is confident enough in the job status variables described above, one will be able to build spell data over job status -i.e indexed by individual and job period- out of the initial wide file. 35961 spells are thus set up-nearly two a person on average[4].

[2] Unlike Taylor (1999)

[3] I aggregate samples A,B,C,D,E and F in the GSOEP terminology

[4] Some spells are right-censored, left-censored and even both[5]. Left-censoring leads to hidden heterogeneity since it clears up the past of the individuals. When setting-up data, one may retort to two fixes. First on can exploit biographical data : parents/education background, career entry and the start of the current job are relatively well known. Second one can focus on young individuals whose parents and childhood were surveyed in the panel tooLet's illustrate now the second fix seen above. All over the study children of surveyed households are kept in track (file 'yKind') and invited to join the survey when they reach the age of 16. In other words

4.3 Descriptives

This section starts with the macro-economic picture of the self-employed. It comes out that the self-employment rate is steady over time in spite of long-term macroeconomic trend such as the East-West reunification and the rise of the unemployment rate. It neither seems correlated with business cycles. At the cohort level, the self-employed rate rises continuously with age below 35 and stabilize above, making the entrepreneurs as a whole looking mature. I found little evidence of generational effects over the twenty-year span of the survey. In a second paragraph I focus on all that happens before the entry on the job market. Consistently with the previous literature, having a father self-employed helps in any case. So does German nationality, though the effect is much more specific to free-lances. Vocational education and craftsmanship are correlated as well as having a higher academic degree and being free-lances. The third subsection portrays the typical careers of the male German workforce. Most importantly, the former jobless seems to be over-represented among the independent. People who turn self-employed tend to do it in their early thirties. Exit rates from self-employment are very high the first four years and abates afterwards. Eventually the decomposition into farmers, free-lances and the rest suggests that the self-employed are a heterogeneous group. Yet it does not undermine the analysis made above : macro-economic steadiness, age pattern, human capital effect and duration patterns.

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the master sample includes people that were surveyed as an adults and whose childhood is -at least partly- known. One extracts this sub-sample (henceforth 'Children' sub-sample) by merging the master sample with the unbalanced panel resulting of the merger of all the 'yKind' file ($Children = MasterSample \bigcap \left\{ \bigcup_{y=1984}^{2003} ykind \right\}$).Thus 2388 out of the 16678 people are kept in. A tabulation shows they mostly get in the main survey around their 16 or 17. They get out in their twenties or early thirties.. I call this sample the 'youth sample' henceforth. There are also purely statistical ways to address the issue of left-censoring -estimating a model with unobserved heterogeneity or a stocksampling model for instance-that will be detailed in the section 4.5 dedicated to estimation. The Youth sample method reduces the sample size too much, so I opted for the master sample, adding biographical data when available and controlling for unobserved heterogeneity.

4.3.1 Aggregated Evidence

The main sample includes approximately 400 independent each year from 1984 to 1999. From 2000 this figure has nearly doubled due to refreshments in the panel that raised the size of the master sample. The share of the self-employed in the workforce lies around 10% over the period -figure 4.1. Compared to the sharp rise of unemployment over the same period -from 5% to 10%- this figure looks flat. Yet a closer examination[6] shows that this figure has risen slightly since the mid-nineties from 9% to 11.2% and cycled around this trend with a two-year periodicity. Part of the trend is due to the reunification of Germany, while the apparent cycles does not seem to be correlated with the IFO business expectation index. Figure 4.3 displays how East Germany catch up its West counterpart in term of self-employment. It started with very low rate of self-employment -merely 4% related to the adverse institutional features of the communist regime- and ends up around 9%. This upsurge can account partly for the global trend but may not suffice since West Germany self-employment rate turns out to rise by its own. An alternative explanation may be that the tightening of the labor market everywhere in Germany increases the incentive to take up one's own business to escape unemployment. In any case the rise of self-employment is small compared to the latter. Figure 4.4 lets see no obvious link between business cycle measure as IFO index and self-employment. This may be accounted by the ambiguous nature of self-employment which could be driven by two opposite forces optimism and unemployment escapism.

I divide the sample into five generations : people born between 1935 and 1944, between 1945 and 1954, between 1955 and 1964, between 1965 and 1974 and between 1975 and 1984. Figure 4.5 compares the self-employment rate by generation for a given year while figure 4.6 does at a given age[7]. It happens that the fifties

[6] See figure 4.4

[7] Defined as the age of the eldest cohort

and older have the highest and the more stable rate of self-employment. Most of those with self-employment plans or ability have achieved their goal. The thirties and forties are in their developing phase. Their rate goes from 2% to 8% -resp 4% and 11%. As I show later, the median age for taking up a business for the first time lies by age 35. The youngest generation's rate of self-employment is still marginal. When reasoning at a given age, the pattern turns out to be consistent across all generations but the oldest that displays lower rate that the next one ten years later.

The proportion of farmers within the self-employed has halved since 1984 while the share of the free-lances has doubled[8]. This increased is obvious after the mid-nineties. Yet, as reported in the previous section, this classification is coarse and must be dealt cautiously.

4.3.2 Background and education

I provide association tables 4.2 between a dummy capturing entrepreneurial experience and dummies controlling for German nationality, father's job status and East Germany background.

The effect of nationality of self-employment is ambiguous in theory. On one hand if the self-employed tend to be insiders, legally, by the diploma or by the informal knowledge of the system, immigrants will have to play harder to compensate the disadvantage of being a 'newbie'. In this case they will be under-represented among the entrepreneur but, as selection was harder, those who are may survive better or longer. On the other hand if the insider power is less strong for creating a business than applying on the job market, the reverse will be true. In the data 3015 individuals have been non-German citizens at some point. Over these 3015 nearly 7.9%

[8]See figure 4.2.

got self-employed one day or another. This figure indicates an under-involvement of non-German citizen relatively to the rest of the population - $13,9\%$. This feature especially prevails among farmer or free-lances. It tends to confirm the first theory. More specifically the obvious under-representation among free-lances may be due to legal restrictions to German citizen or lack of acknowledged diploma for certain professions : doctors, lawyer and so on. Yet the impact of this story is very limited at this stage. It does not reason ceteris paribus. Furthermore the nationality variable does not take into account the current nationality, the emigration country, the time spent in Germany, or the desire to become German.

Having a father self-employed is deemed to be helpful by the previous literature. First the child will have a role model and a 'free' self-employment experience that may lower his own risk aversion or give him entrepreneurial traits. Second when an adult he will be able to ask his father for entrepreneurial advise. Last the father may bequest his firm[9]. In any case it helps. In my data it happens that entrepreneurs' sons have twice as much chance as the others to get self-employed themselves at some point. Each category is affected : one doubles one's chance to become a free-lance, a craftsman or a shopkeeper if his father is a self-employed while it virtually must be so if he wants to be a farmer -0.5% chance if not versus 9% chance if yes. However I cannot check what kind of self-employed was the father, neither whether entrepreneurs' sons create their own businesses or just inherit those of their fathers.

The economics of self-employment in transition economy like East Germany is a field apart. If transition economy are marred with unemployment, and if self-employment provides the jobless with an alternative living, entrepreneurship will be abundant. On the other hand, people might not have the self-employment 'reflex'. In that case

[9] This case is often excluded because it means no business creation. I am not able to do the distinction here.

entrepreneurship will be scarcer. In the sample having an East German background slightly lowers the chance of being self-employed, even if the aggregated share of entrepreneurs in workforce is on the rise[10]. The probability goes from 15% to 12% for entrepreneurs as whole, hardly varies for craftsmen and shopkeepers, goes from 5% to 3.5% and is divided by three for farmers.

The type of education (vocational, academic, mix of both) is to determine the sector in which one will work. So for the business opportunity. Besides, within each education track a higher degree may make a difference for both the job market and business opportunity[11]. Education by self-employment status is available figure 4.7. The self-employed seem to have received more education than the main sample -only 5% vs. 14% have received elementary education only or are still in school. Higher education is especially frequent -28% vs 18%- among them. The share of vocational increases as well. The picture is yet contrasted within the independent. As expected more than 60% of the free-lances hold a higher academic degree while 20% of those reported as 'Others' do. Meanwhile mid-vocational is over-represented -47%- among the 'Others' category. If type of education seems to be linked with entrepreneurial opportunity later on, it seems that -at least for vocational education- the higher one goes, the higher are the chance of being self-employed. This will be confirmed by the probit estimations.

4.3.3 Career Dynamics

I focus now on the events occurring once an individuals enter the job market : age at business entry, duration in self-employment[12] and transition probability from

[10] As seen in the previous subsection.

[11] Think of basic vocational education and higher vocational education.

[12] As previously said, from 16678 individuals one gets 35961 job spells. Each individual experiences two spells on average during the survey but in practice this figure varies more over the sample. Out of this 35961, 2246 observations are self-employment spells. Censoring is even more

one job status to another over a decade.

In terms of age at entry, it turns out that the quartile ages -respectively the first quartile Q1, the median M and the third quartile Q3-for starting a business are $29-35-44$ while the Q1-M-Q3 ages for starting a business **for the first time** is $28-34-44$[13].The background variables seemingly do matter.

In terms of duration in business nearly 85% of the uncensored spells shut down before four years. I draw survival plot by censoring status -figure 4.8- and by self-employment type -4.9. Note that the first year turns out to be the most risky. This is even more striking for free-lances who undergo a more than 50%+-hazard rate the first year. In any case the hazard rate go down sharply. The uncensored spells are shorter by construction. This conclusion would need to be investigated more thoroughly by surveying the cause of business termination[14] and estimating proper duration models[15].

Transition matrices between the eight possible job status are provided -tables 4.3 and 4.4- for the decades 1984-1994 and 1994-2003. It sheds light on the categories which entrepreneurs in 1994 (resp 2003) are likelier to come from as well as the career ten years on of those who were independent in 1984 (resp. 1994). Regarding the first question and the first period it turns out that the unemployed and the students (vs. apprentices) are the likeliest to own a business ten years later. The apprentices look surprisingly little keen to do so. They become more employees instead. In

severe than in the full sample (see 4.7) . Focusing on uncensored spells is hardly a fix,since they stand for the very specific businesses that terminated during the -possibly short- span of observation.

[13]The absence of in-depth job biography affects deeper the latter than the former. Mechanically one may wrongly take the first observed spell as the first ever.

[14]But -as discussed in Section 4.2- this option seems to be out of touch for now

[15]See .

the second period the students and apprentices rates seem to converge around 5% far below the unemployed one which lies between 10% 15%.A closer examination shows tables 4.5 and 4.6 that those labeled as students overwhelmingly got free-lance during the first decade while those called apprentices exclusively went to the 'Other' category. The picture is less contrasted in the second period. These facts are consistent with the broad idea that the student term denoted people studying in academia and to be (self)-employed in the tertiary sector while the apprentices are practicing in vocational schools before getting craftsmen, shopkeepers and so on[16]. Regarding the second question (what happened to entrepreneurs) it comes out that this category is the most elusive of the three 'sustainable' working categories - self-employment,employment and civil-service- . Only 66% in the first decade and 55% for the second one are still self-employed ten years later. Yet they less risk unemployment over the two periods (around 4%).

4.3.4 Heterogeneity

The categories available in the GSOEP show mixed evidence of heterogeneity. Most of patterns are robust : role of human capital transmitted by the father, edu-

[16]Yet this idea does not account for the tiny share of apprentices that get self-employed in the first decade. Maybe -due to macro effects- during the first decade the free-lance sector had offered more opportunity than the 'Other' one, pulling the apprentices out of self-employment. The small size of the effective sample is another explanation. Among the people surveyed between 1984 and 1994 hardly 195 and 125 individuals are respectively students and apprentices in 1984. Between 1994 and 2003 these figures go to 170 and 125. If 5% of them look to get self-employed, this leads to a sample of interest of -at best- a dozen of people. That is obviously too small to draw any firm conclusion : large standard errors are unavoidable while over-under-weighting effects and local definition inaccuracy are magnified. One example of this variability effect are the data for the unlikely transition from apprenticeship to academia. It is reported as 20.7% of the apprentices over the first decade and a mere 0.6% over the second. In term of people it respectively means 8 and 1 individuals. One straightforward computation shows that the weighting tends to over-represent the former and underestimate the latter. When focusing on the 8 more closely, one notes that all of them were under 20 in 1984 : their 1994 academic formation could be a *'Meisterschaft'* formation, misreported somehow.

cation, duration and broad income profiles. Yet the intensity of such phenomenon changes from a category to another. In other words if interested in sign of such effect one may consider the self-employed as whole but if looking for quantitative estimates one had better split them up into categories. In respect to public policy, the variation in intensity across the categories of self-employed may imply differences in the repartition of the efforts done by policymaker. For instance, if free-lances are more 'intensive' in human capital for instance and if the education they need is higher academia, the public policy will have to stress higher academia. In any case this analysis represents a step toward understanding heterogeneity among entrepreneur. A deeper understanding will require finer classification and is left for another occasion.

4.4 Model and identification

I generalize the analysis conducted above. I model the transition from one job status to another over year. Many approaches are feasible -markovian, proportional hazard- and all of them can be encompassed in a general maximum likelihood set-up. Here I choose a markovian model exploiting the long file built up from the main sample in which each observation is identified by an individual and a year. I restrict my attention to three transitions : employment to self-employment, unemployment to self-employment, and self-employment to self-employment[17], each of them on a yearly basis. I denote $\theta_{SE,SE}$ the probability to stay self-employed over the year, $\theta_{SE,E}$ the probability of jumping from employment to self-employment and $\theta_{SE,U}$ the probability to become independent within the year after unemployment. Estimating the impact of human capital on these three probabilities is carried out by partitioning the long-file in three groups (respectively cells of self-employment, unemployment and unemployment) before estimating a probit model of the probability of being self-employed the year after for each of these groups. In a markovian set-up without

[17] In other words survival in self-employment.

fixed or random effects the three estimation can be made independently :

$$
\begin{aligned}
P(s_{it+1} = SE|s_{it} = SE) &\sim \Phi(BK_i\beta_{BK} + ED_{it}\beta_{ED} + T^S_{it}\beta_{ED} + E^S_{it}\beta_S + E^U_{it}\beta_U + AGE_{it}\beta_{AGE} + ENTRY_i\beta_{ENTRY}) \\
P(s_{it+1} = SE|s_{it} = E) &\sim \Phi(BK_i\beta_{BK} + ED_{it}\beta_{ED} + T^E_{it}\beta_{ED} + E^S_{it}\beta_S + E^U_{it}\beta_U + AGE_{it}\beta_{AGE} + ENTRY_i\beta_{ENTRY}) \\
P(s_{it+1} = SE|s_{it} = U) &\sim \Phi(BK_i\beta_{BK} + ED_{it}\beta_{ED} + T^U_{it}\beta_{ED} + E^S_{it}\beta_S + E^U_{it}\beta_U + AGE_{it}\beta_{AGE} + ENTRY_i\beta_{ENTRY})
\end{aligned}
$$

BK_i are background variables, namely father's job status and i's nationality. ED denotes education variables : dummies for *'Meister'* and higher academic education and linear variable for degrees in vocational education[18]. Then come tenure in the current spell (self-employment, employment or unemployment) and years of experience in previous spells as an independent E^S_{it} or a jobless E^U_{it}. Other controls are added such age, age at entry and so on. The first is about business survival in general. The second transition answers the question 'who goes from unemployment to self-employment' in term of background and experience.If unemployment experience is included, this estimation emphasizes the fate of former jobless in business. The third is just the traditional transition from employment to business and is useful as check : I can verify whether its estimates are in line with those of the previous literature. The first series explanatory variables, that is father's job status, nationality and geography identifies the part of social or job mobility which is out of reach of public policies. On the other hand, the second series -education variable- can be supported and the model aim at identifying its effect on job mobility. At last the tenure and experience is supposed to identify the on-the-job formation. We discuss identification hereafter.

Several concerns come out here. First, my education variables are possibly endogeneous. According to conventional wisdom, people choose their education and their

[18]Namely 0 for no vocational education, 1 for the basic level of vocational education, 2 for basic vocational education and high school final education (Abitur) and 3 for higher vocational education

first job experience regarding their future prospect and what they know of their own abilities. In other words education is not causal relatively to self-employment : there are variables of ability and taste -usually unobserved by the researcher- that may determine education and occupational choices simultaneously. Nevertheless -on the interaction between education and self-employment- one may argue that one can become self-employed whatever the level of studies and that the hidden heterogeneity that enable one to attain a given degree is likely to be uncorrelated with which makes one an would-be entrepreneur like risk aversion or tightness of credit constrain for instance. This claim is convincing for variables making a very broad distinction in education : dummy for vocational, academia. On the other hand, it is very arguable for those controlling for very specific case like having a 'Meister'. Therefore this variable remains under strong suspicion. Second my experience variables are left-censored. Variables of job experience are stock variables that would require the whole job biography to be worked out without bias. Alas if one has access to the unemployment biography of each individuals since the age of 15, pre-survey biography is quite thin regarding self-employment. The resulting heterogeneity can be address in several ways : amending unemployment variable with pre-survey spell, adding random effects or simulating the evolution of the censored variable[19].

The third possible weakness of the model is the absence of reliable physical capital measurements. If I exclude control for wealth -as people who experience more unemployment spells are likely to be less able to save- it may be more difficult to disentangle the human capital effect of past job experience from its wealth effect. From a general point of view dealing with wealth or past incomes is tricky. The data that are often error-prone. More essentially, these variables are strongly endogenous to the carrier choices. For instance, one who plans to get self-employed at some points is likely to save more -to escape the credit constrain- than the one who

[19]In a previous version of this paper I estimated a stocksampling model

does not (See Buera (2003)). Those with higher wages may share some unobserved features with the successful entrepreneurs and so on. In any case, the estimates may suffer from an upward bias. That is why instrumental strategies have been developed so far. The researcher looks to observe the effect of unexpected incomes-large enough to change the one's condition toward credit and unrelated to hidden abilities suspected to affect willingness to undertake. Big inheritances -see for instance Hurst et al (2004), Joulfaian et al. (1994) or Holtz et al. (1993), real estate added values are fair candidate to target the middle class people who can have entrepreneurship ambition, well-off enough to accumulate over a pair of generation but not that wealthy to do without generational help. Unfortunately the GSOEP records either strongly endogenous variables such as dummy for various form of capital ownership and income, or weak instruments as inheritance received or unexpected income[20]. I call the latter weak instrument because their amount is usually too small to make a difference in term of investment and occupational choices. I run some estimation with these variable in section 4.6.3.

To address the three concerns, I proceed as follows. First I run a basic model including education and background variables only. Second I add censored experience variables without any control for the censoring. Third I control for the age at which one entered the survey as a rough safeguard for left-censoring. Fourth I address left-censoring by amending variables if possible[21]. All of these is done in Section 4.5. In section 4.6, as a robustness check, I run a version of my model replacing time-constant variable by random effects. I also quickly discuss what happens when capital variables are included.

[20] Moreover a few year only.
[21] Using biography file for unemployment experience for instance.

4.5 Results

One will find table 4.8, 4.9 and 4.10 the probit estimates of 4.1[22]. For each transition I display six estimations. First, columns (a) include all the variables that are neither endogenous nor left-censored for sure : background variables, tenure in the current state and age. Conversely I let out all the variables that may be endogenous or left-censored or that control for left-censoring : unemployment and self-employment experiences, age at entry, dummy for *'Meisterschaft'*. In this column, I also excluded the IFO index that controls for macro-environment because the data have been available since 1991 only. In the second estimation -columns (b)- experience variables are added. To control for left-censoring, I include age at entry and then correct unemployment experience with biographic data -in respectively columns (c) and (d)-. *'Meisterschaft'* dummy and business climate are shown in column (e) and (f). Most of coefficients are stable over the columns which tends to soften the concerns described above. Virtually all background and education variables have a positive -and often significant-effect.

Let describe the estimations related to the transition from employment to self-employment -table 4.8. The average probability to jump from employment to self-employment is 1.1% a year . Estimations are run on 56887-columns (a) to (c), 45707-columns (d) and (e)- and 29065 when controlling for business climate column (f). Having a father self-employed increases on average by 50% the probability to become independent each year. Consistently with the previous literature this figure is significant in the first five columns. It diminishes slightly from 60% to 40% when previous self-employment is included. Indeed these variables may be colinear somehow : those with an independent father are likelier to jump to self-employment and

[22] Table 4.8, 4.9 and 4.10 show the marginal effect of each regressor on the related probabilities $\theta_{SE,W}$, $\theta_{SE,U}$ and $\theta_{SE,SE}$.

to have already been self-employed over the past, making father status and previous self-employment experience partly redundant. The effect of German nationality is fairly the same numerically and even more significant statistically as suggested in the descriptive section. One more degree [23] in vocational raises by 20% the probability of becoming independent over the year. By comparison higher academic education increases by 100% or even 150% this chance. *'Meisterschaft'* dummy accelerates by 80% at best but this figure is significant only in column (e). Tenure in employment has a significant negative impact : one more year spent reduces by 10% the probability of entering business. As tenure increases, wage rise and position specific human capital make people more 'conservative' : the more comfortable the place gets, the harder taking up one's own activity is - conventional wisdom says. Previous experience as an independent raises the probability by 30% each year. This figure falls to 20% when correcting experience variables by biographic data. Yet the standard error fall even more, making the effect more significant. One may generalize this finding and assume the left-censoring amplifies coefficient and standard error, implying that the bias on the t-stat is ambiguous and at best 'conservative'. Past unemployment experience seems to accelerate the transition. Numerically the effect is lesser than the self-employment experience but still amounts to 10%if correcting by biographic data and to 20% otherwise. An explanation for this phenomenon is that unemployment enhances people's stamina to risk. Another could be that people who are more prone to unemployment have less opportunity on the job market and thus are more incited to create their own position. Surprisingly business cycles seems to have no significant effect. At last when taking apart the transition from unemployment to free lance status one finds out that most effects remain and are often magnified, especially the impact of higher education.

[23] there are three degree in the GSOEP classification

I focus now on the transition from unemployment to self-employment shown table 4.9. The average probability of setting up a business among the jobless lies between $2,4\%$ and $2,7\%$ a year. The number of observations amounts to 5942 for estimations (a) to (c), 4013 for estimation (d) and (e) and 2818 for the (f). Though derived from a smaller sample size, the estimates are often as significant as those of the transition from employment to self-employment. They are also bigger numerically. Father's occupation increases the probability of doing the transition by 100% in estimation (a). This figure drops to 65% in the last one -column (f)- and becomes non significant. Being German speeds up here by 50% the transition in column (a). Once again these estimates fall both numerically and statistically when adding control. It is only significant in the first three columns. One more vocational degree brings between 30% and 50% more chance to get independent over year. Higher education effect on the other hand amounts to nearly 50%. All these estimates are significant no matter the specification. *'Meisterschaft'* dummy is not significant though it numerically raises probability by 40% at least. Tenure has positive impact this time. Numerically one more year increases by 10% the transition toward self-employment. Yet this estimate is never significant. According to the conventional wisdom the longer an individual is jobless, the less help he gets from the state and the less opportunity he has on the job market. Therefore he is more likely to consider entrepreneurship. Previous self-employment experience helps by 50% at worst but is never significant. Past unemployment experience - let alone the current one- has a significant negative impact on the transition probability -around -25%- at least if not correcting by biographical data. Unlike tenure in unemployment, the more period of self-employment one has, the less keen one is to take up a business. Maybe those people are less discouraged to be hired as they know from past experience they could be so. This point is not clear at this stage yet. Once again business climate seems to have no effect seemingly.

Third I describe the transition from self-employment to self-employment over year, table 4.10. I avail myself of 6490 observations in the first three estimations, 5430 in the next two and 3833for the last. On average 84%remains self-employed over a year. Background controls but higher education are not significant or hardly significant statistically. Higher education raises survival probability by 5% in most of estimations and even by nearly 10 when all controls added -column (f)-. Father's occupation turns out to matter less than previously. The estimates are significant in columns (a) to (c) and the numerical effects lie around 5% then . On the other hand tenure is hugely significant. One more year in self-employment brings up to 2% a year in term of probability to stay. In term of hazard of quitting it implies an increase of nearly 10%. The risk of quitting self-employment is much higher at the beginning of the venture and decreases with tenure. Counter-factual hazard rates are drawn hereafter. When tenure is given, previous experience has a negative impact. It could seem surprising. Yet having had a previous spell of self-employment means having quitted that spell at some point and so being maybe more prone to failure : people with positive previous experience are in their second try at least. To test this assumption one can control for the number of spells of self-employment experienced before the current one. In that case experience in year will get a positive impact while the number of spells of self-employment experienced previously will have a negative one. Here one year of previous experience -tenure fixed- decreases by 1.2% the chance of survival. Unemployment has no impact when corrected-column (d) to (f)- and a negative one otherwise -column (a) to (c)-. In other words if the unemployed get more self-employed, they may struggle more for keeping up when self-employed. One can now draw the hazard against the tenure in case of interest. Table 4.13 displays the hazard rate for a German citizen, son of two employees, who has a higher vocational degree and a *'Meister'*, enters the survey at 20 and starts his first business at 25 after having been employee in a period where the business cycle is quite high. The 95% confidence envelop is computed assuming the initial rate is perfectly known. In table 4.14 one lets vary a variable at a time around this basic case : (1)'s father was self-employed, (2) got an higher academic education instead of a vocational, (3) is 35 and was an entrepreneur during 4 years.

4.6 Extensions

4.6.1 Results by category

In Table 4.11 the self-employed have been split by category and re-run the probit estimation of the probability to stay in business yearly - table 4.10 column (d). The effect of father's status -not significant for the self-employed as a whole- turns positive for the shopkeepers and the craftsmen. He is positive and not significant for the farmers and negative and not significant for the free-lances. Nationality seems to have no impact as for the sample as whole. Vocational education has still no clear impact. Unsuprisingly higher education -that appeared to have a positive effect on business survival in general- has its strongest impact on the free-lances. It nearly doubles the chance of survival each year. Tenure has a positive significant effect everywhere. Numerically it matters more for the free-lances than the rest : the marginal effect go from 0.12 and 0.15 for the farmers and the craftsmen to 0.023 for the free-lances. The other marginal effects are not significant as in the general estimation.

Eventually, most of the evidence found on the self-employed as a whole are still true on each category. Nevertheless the free-lances are subject to higher effect than the farmers and the craftsmen.

4.6.2 Random effects

Although many controls have been included in the estimations of 4.1, the existence of unobserved types with regard of self-employment entry cannnot be rule out. Unobserved heterogeneity may arise from hidden educational background (lack of accuracy of education variable), censored experience due to panel design or psychological characteristics such as risk aversion. To address this issue I run an random effect model of 4.1. For the sake of identification, I exclude the time-constant or near time-constant variables like background and education that will be capture in the random effects as unobserved heterogeneity. The remaining variables are macro-environment, tenure experience variables. It happens that the related coefficient are not changed. In other word unobserved may exist but does affect the effect of time varying variable.

4.6.3 Effect of past/permanent income and asset

The GSOEP provides many different tracks of income and asset. For the sake of robustness, I take advantage of this diversity. From yearly incomes I work out a rough accumulated wealth. I have also access to inheritance and unexpected earnings since year 2000 in the GSOEP. For each transition of 4.1 I run eleven estimations, one by asset variable[24].

In any case the estimates of 4.1 remain virtually unchanged. This is even true for experience variables. As including asset variables reduces the sample size, it also reduces precision. The effect of accumulated income is positive and significant. Inheritance has a positive but not significant effect which is consistent with the

[24]First I use personal-equivalent household yearly income before and after taxes, accumulated or lagged, in level or in log. Hence the first eight specifications. Note that the lagged income stands for the polar case where the individuals is extremely impatient $\delta = 0$. Conversely the accumulated income stands for the case where she saves everything $\delta = 1$. Second I replace wealth by a dummy for inheritance. Finally I include unexpected gain in level or log.

assumption that this variable is a weak instrument.

4.7 Conclusion

Education can make a difference for the business entry of both employee and unemployed even if -consistently with the previous literature -family background effect remains strong. It happens also that the jobless try more frequently to start up their ventures. Vocational education is helpful to become an entrepreneur in the secondary sector mainly. On the other hand higher academic education opens the door to free-lance self-employment. At the end of the day the effect on the latter is stronger than that on the former. In term of public policy it implies that the policymaker could support free-lance self-employment first. However the effect on business survival is less clear : tenure seems to be the only significant -positive- factor.

	No	Yes	Total
No	11617	7666	19283
	32.3	21.3	53.6
Yes	7666	9012	16678
	21.3	25.1	46.4
Total	19283	16678	35961
	53.6	46.4	100

Tab. 4.1 – Right censorship and left censorship in spell data

4.8 Appendix

4.8.1 Descriptives

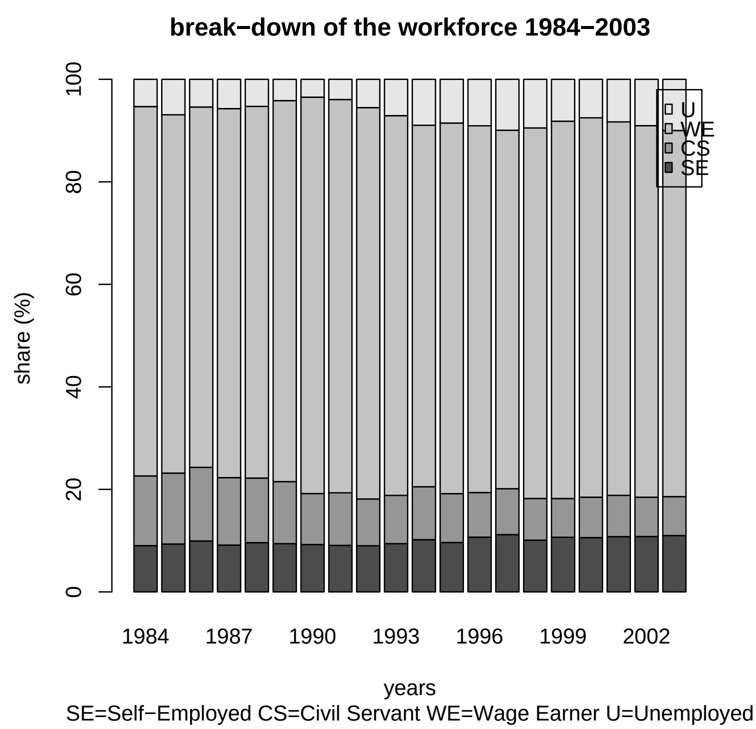

Fig. 4.1 – Share of the self-employed within the workforce

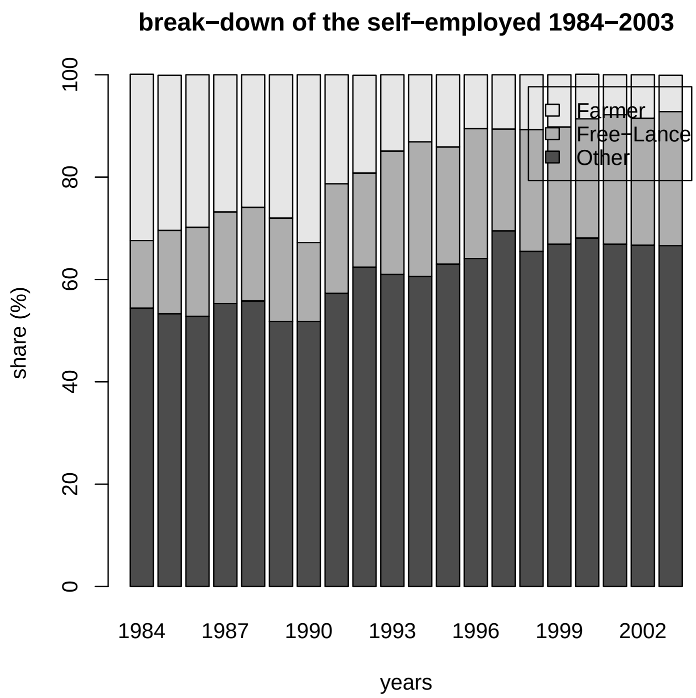

FIG. 4.2 – Share of farmers, free-lances and the others, among the independent

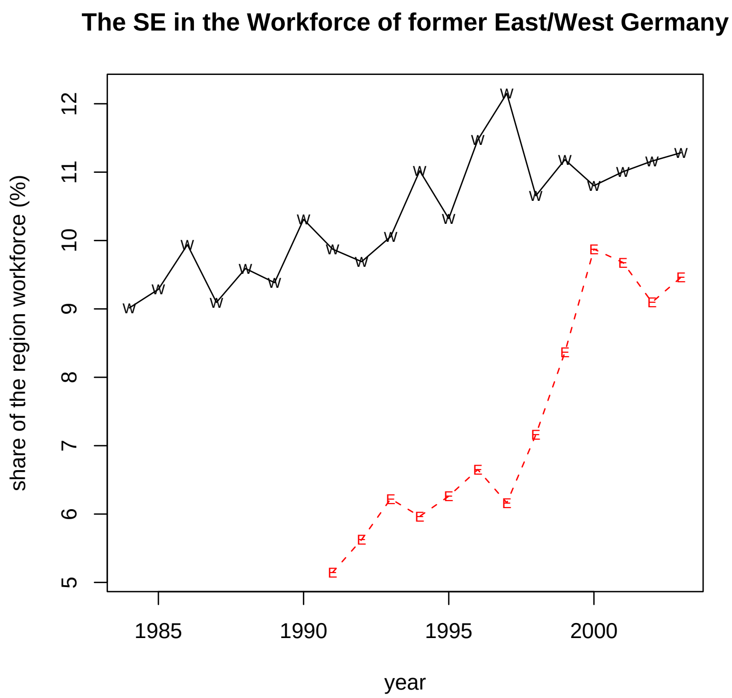

FIG. 4.3 – Share of self-employed among the workforce of East-West Germany

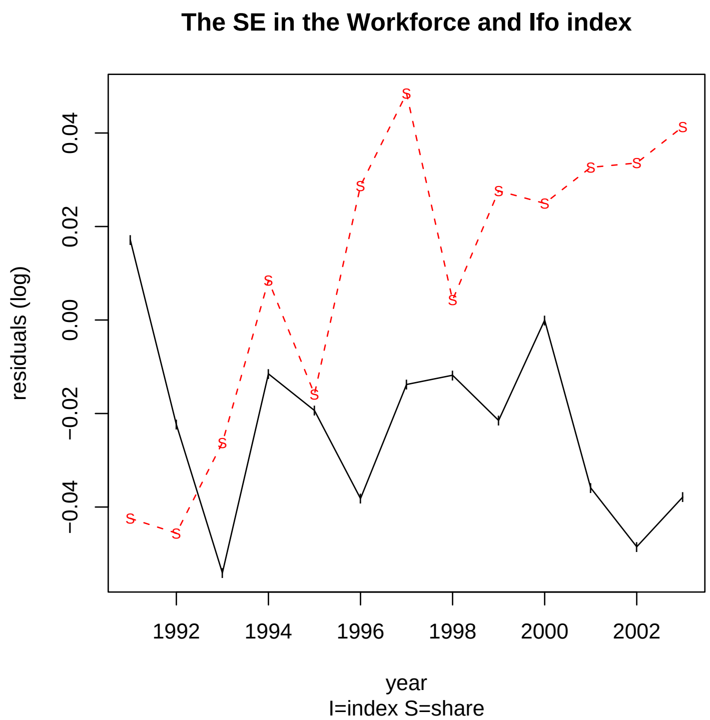

FIG. 4.4 – Share of self-employed and the IFO index

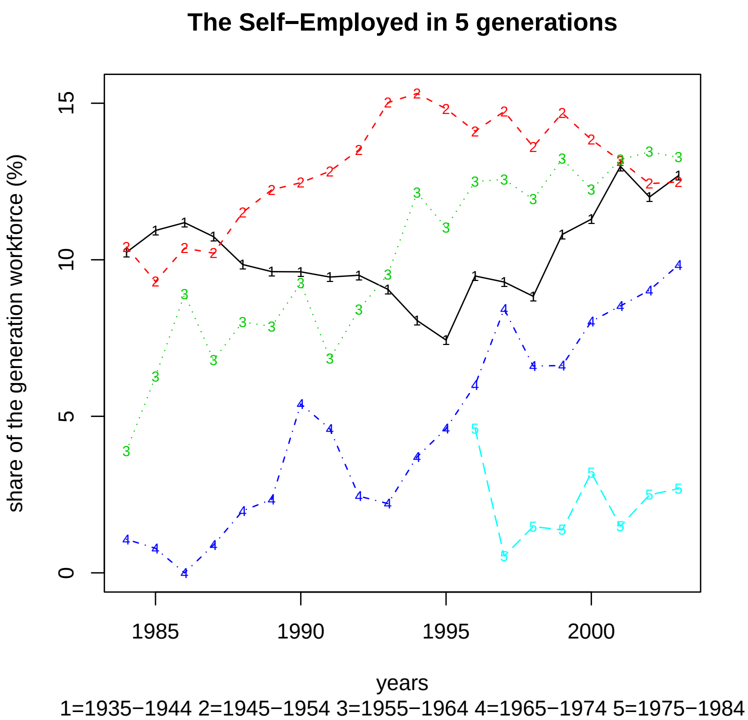

Fig. 4.5 – Share of self-employed among the workforce of five generations

FIG. 4.6 – Share of self-employed among the workforce of five generations by age of the eldest cohort

	Whole sample	German ever	non-German	Father not SE	Father SE	West ever	East Back.
SE once+	13.7	14.4	7.9	11.5	30.8	14.1	11.8
Farmer once +	1.6	1.7	0.2	0.5	9.6	1.8	0.5
FL once+	4.9	5.2	2.4	4.3	9.3	5.2	3.4
Other SE once +	10.4	10.9	5.9	9.3	18.7	10.6	9.4

Tab. 4.2 – Background and selection into self-employment (%)

	Pens. 1984	Inac.	Stu.	App.	Une.	Emp.	Civ.	Self.
Pens. 1994	-	50.7	-	-	7.2	10.7	7.8	13.8
Inac.	-	5.3	2.2	1.4	12.3	2.6	5.4	0.7
Stu.	-	0	12.7	20.7	1.3	0.2	1.5	-
App.	-	0.3	1.1	-	3.0	0.1	-	-
Une.	-	5.8	3.2	3.5	17.1	6.5	2.2	4.0
Emp.	-	20.4	57.6	68.3	50.7	74.2	14.4	14.7
Civ.	-	-	10.5	5.1	-	0.4	63.9	-
Self.	-	17.5	12.8	1.1	8.5	5.4	4.8	66.9
Total	100	100	100	100	100	100	100	100

Tab. 4.3 – Job status transition matrix from 1984 to 1994 -relative population frequency

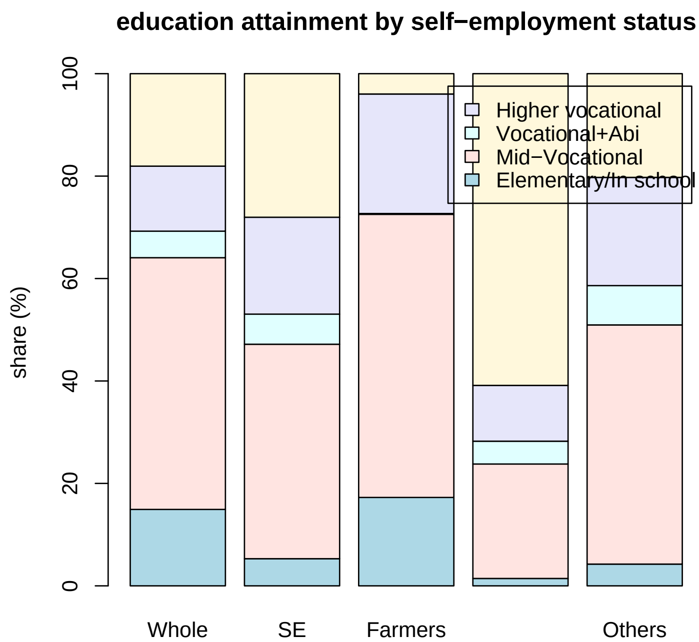

FIG. 4.7 – Educational attainment by self-employment status

	Pens. 1994	Inac.	Stu.	App.	Une.	Emp.	Civ.	Self.
Pens. 2003	95.9	20.2	-	1.0	33.1	17.0	15.7	12.5
Inac.	-	24.5	1.8	1.2	0.6	0.7	-	1.4
Stu.	-	-	8.8	0.6	0.2	0.1	0.7	0.33
App.	-	-	3.0	-	0.2	0.2	-	0.3
Une.	2.2	9.4	6.1	12.4	16.1	7.0	0.3	3.3
Emp.	1.1	31.3	73.7	75.2	39.5	69.9	24.1	25.9
Civ.	-	-	1.4	4.0	-	0.8	53.5	0.6
Self.	0.8	14.6	5.0	5.6	10.4	4.5	5.7	55.6
Total	100	100	100	100	100	100	100	100

TAB. 4.4 – Job status transition matrix from 1994 to 2003 -relative population frequency

	Stu. 1984	App.	Une.
Farm. 1994	16.3	0	0
free-lances	57.6	0	60.6
Other	26	100	39.4

TAB. 4.5 – (Student+Apprentice+Unemployed)->(Self-employment types) transition matrix from 1984 to 1994-relative population frequency

	Stu. 1984	App.	Une.
free-lances 2003	52.5	15.5	4.5
Other	47.5	84.5	95.5

TAB. 4.6 – (Student+Apprentice+Unemployed)->(Self-employment types) transition matrix from 1994 to 2003-relative population frequency

	No	Yes	Total
No	548	343	891
	24.4	15.3	39.7
Yes	584	771	1355
	26	34.3	60.3
Total	1132	1114	2246
	50.4	49.6	100

TAB. 4.7 – Two-way table between dummies 'Left-censored spell' and 'Right-censored spell' -sample relative frequency

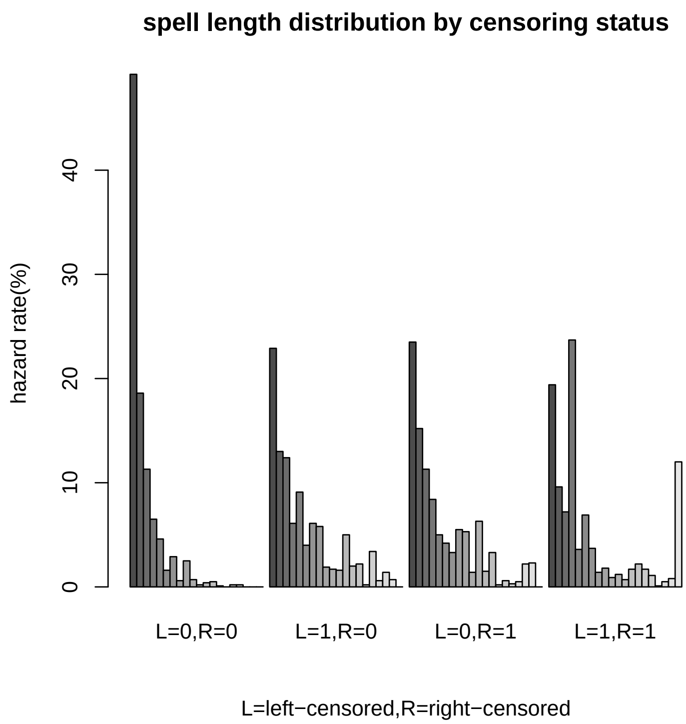

FIG. 4.8 – Duration of self-employment spells by censoring status

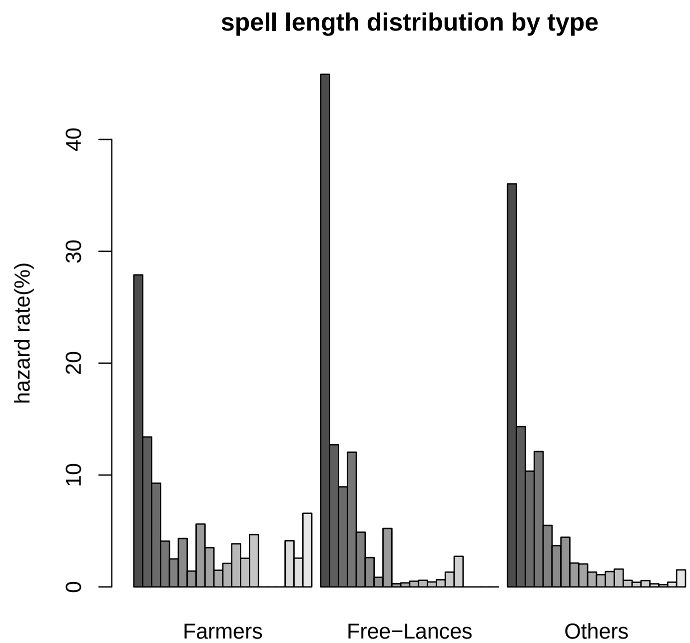

FIG. 4.9 – Duration of self-employment spells by type

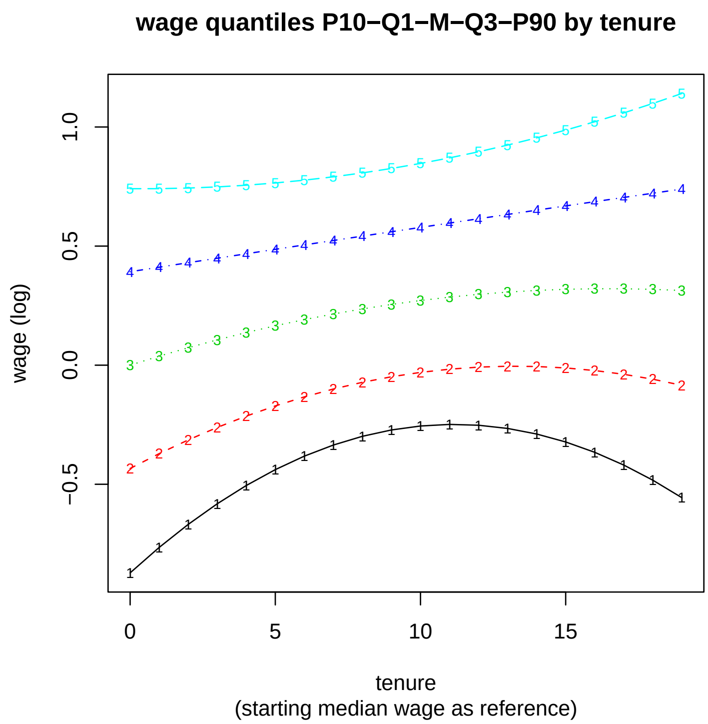

FIG. 4.10 – Wage quantiles P10-Q1-M-Q3-P90 by tenure in employment

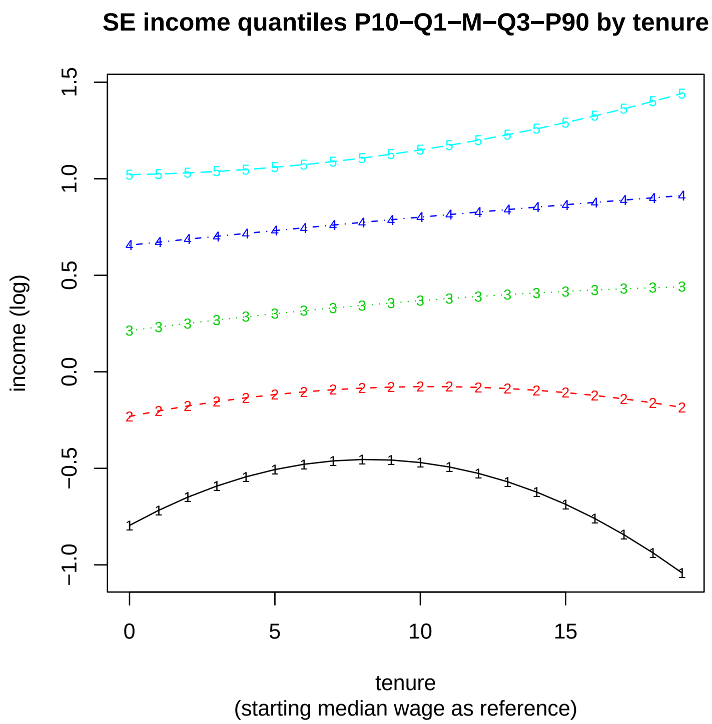

FIG. 4.11 – SE income quantiles P10-Q1-M-Q3-P90 by tenure in business

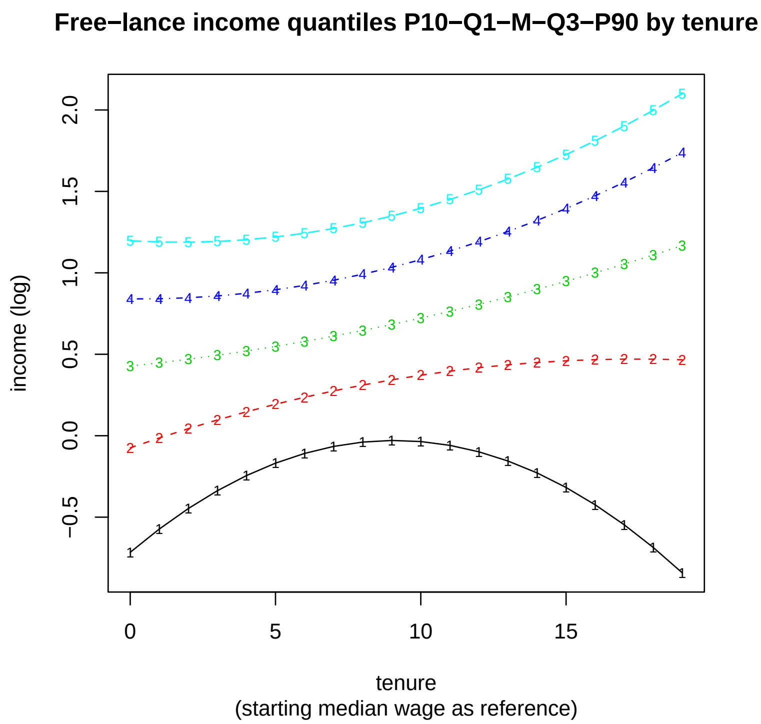

FIG. 4.12 – Free-lance income quantiles P10-Q1-M-Q3-P90 by tenure in business

	(a)	(b)	(c)	(d)	(e)	(f)
Father's	0.006	0.004	0.004	0.005	0.004	0.003
Status	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
German	0.005	0.004	0.004	0.004	0.004	0.004
nationality	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Vocational	0.003	(0.002)	(0.002)	(0.002)	(0.002)	0.001
Education	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
'Meister'					0.008	0.006
					(0.004)	(0.004)
Higher	0.014	0.014	0.013	0.01	0.01	0.009
Acad. Educ.	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Tenure	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
SE previous		0.003	0.003	0.002	0.002	0.002
experience		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Une. previous		0.002	0.001	0.001	0.001	0.001
experience		(0.001)	(0.001)	(<.001)	(<.001)	(<.001)
Age	0	0	0	0	0	0
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Age at			0	0	0	0
entry			(<.001)	(<.001)	(<.001)	(<.001)
Business						-0.005
Cycle						(0.017)
P.obs	0.011	0.011	0.011	0.011	0.011	0.011
N. obs	56887	56887	56887	45707	45707	29065

TAB. 4.8 – Year-to-year transition form employment to self-employment : marginal effects - unemployment experience amended with biography in column (d),(e) and (f)- (s.e. in brackets)

	(a)	(b)	(c)	(d)	(e)	(f)
Father's	0.023	0.024	0.022	0.019	0.019	0.018
Status	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.016)
German	0.009	0.009	0.008	0.008	0.008	0.006
nationality	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)
Vocational	0.01	0.009	0.008	0.007	0.007	0.007
Education	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
'Meister'					0.019	0.009
					(0.022)	(0.019)
Higher	0.126	0.115	0.107	0.128	0.128	0.144
Acad. Educ.	(0.038)	(0.036)	(0.031)	(0.044)	(0.044)	(0.054)
Tenure	0.001	0.001	0.001	0	0	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
SE previous		0.001	0.001	0.002	0.002	0.001
experience		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Une. previous		-0.004	-0.005	0	0	-0.003
experience		(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Age	-0.001	-0.001	0	0	0	0
	(<.001)	(<.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age at			-0.001	-0.001	-0.001	-0.001
entry			(0.001)	(0.001)	(0.001)	(0.001)
Business						0.051
Cycle						(0.081)
P.obs	0.023	0.023	0.023	0.024	0.024	0.027
N. obs	5942	5942	5942	4013	4013	2819

TAB. 4.9 – Year-to-year transition form unemployment to self-employment : marginal effects - unemployment experience and tenure amended with biography in column (d),(e) and (f)-(s.e. in brackets)

	(a)	(b)	(c)	(d)	(e)	(f)
Father's Status	0.028	0.029	0.028	0.027	0.027	0.005
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.019)
German nationality	0.034	0.038	0.037	0.036	0.036	0.019
	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)	(0.026)
Vocational Education	0.007	0.006	0.007	0.007	0.006	0.013
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.01)
'Meister'					0.017	0.031
					(0.029)	(0.03)
Higher Acad. Educ.	0.037	0.036	0.039	0.051	0.051	0.078
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)
Tenure	0.014	0.013	0.015	0.016	0.016	0.016
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SE previous experience		-0.014	-0.011	-0.01	-0.01	-0.008
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Une. previous experience		-0.009	-0.005	0.002	0.002	0.001
		(0.008)	(0.009)	(0.003)	(0.003)	(0.004)
Age	0	0	-0.003	-0.003	-0.003	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Age at entry			0.002	0.003	0.003	0
			(0.002)	(0.002)	(0.002)	(0.002)
Business Cycle						-0.138
						(0.207)
P.obs	0.845	0.845	0.845	0.848	0.848	0.844
N. obs	6490	6490	6490	5423	5423	3833

TAB. 4.10 – Year-to-year probability to stay in self-employment : marginal effects - unemployment experience amended with biography in column (d),(e) and (f) - (s.e. in brackets)

	Famers	Free-Lances	Others
Father's	0.073	-0.027	0.033
Status	0.05	0.043	0.018
German	0.137	-0.038	0.048
nationality	0.162	0.047	0.027
Vocational	0	0.033	0.014
Education	0	0.027	0.009
Higher	-0.022	0.136	0.054
Acad. Educ.	0.019	0.053	0.025
Tenure	0.012	0.023	0.015
	0.006	0.006	0.003
SE previous	-0.028	0.008	-0.011
experience	0.016	0.013	0.005
Une. previous	0.005	0.009	-0.004
experience	0.007	0.008	0.004
Age	-0.01	0.001	-0.004
	0.006	0.004	0.002
Age at	0.007	0.001	0.003
entry	0.006	0.003	0.002
P.obs	0.877	0.839	0.84
N. obs	549	1079	3779

TAB. 4.11 – Year-to-year probability to stay in self-employment by category : marginal effects - unemployment experience amended with biography (s.e. in brackets)

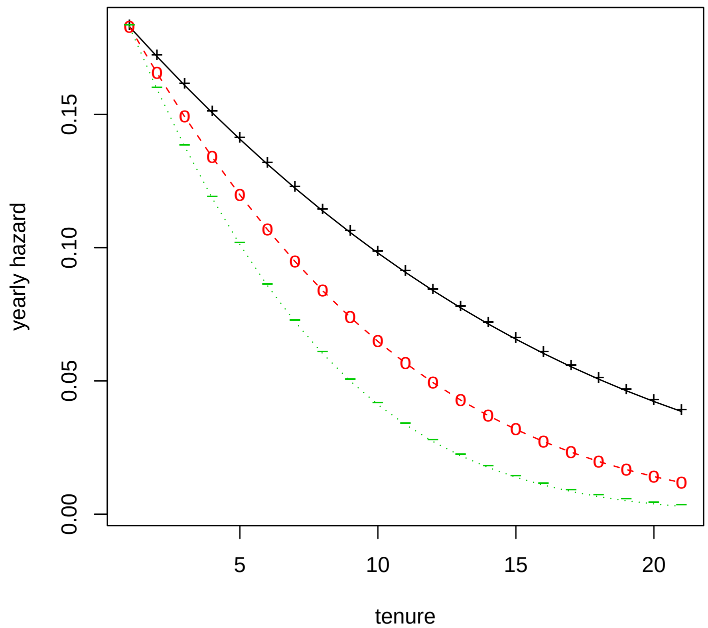

FIG. 4.13 – Baseline hazard of quitting self-employment for a probit model controlling for linear tenure

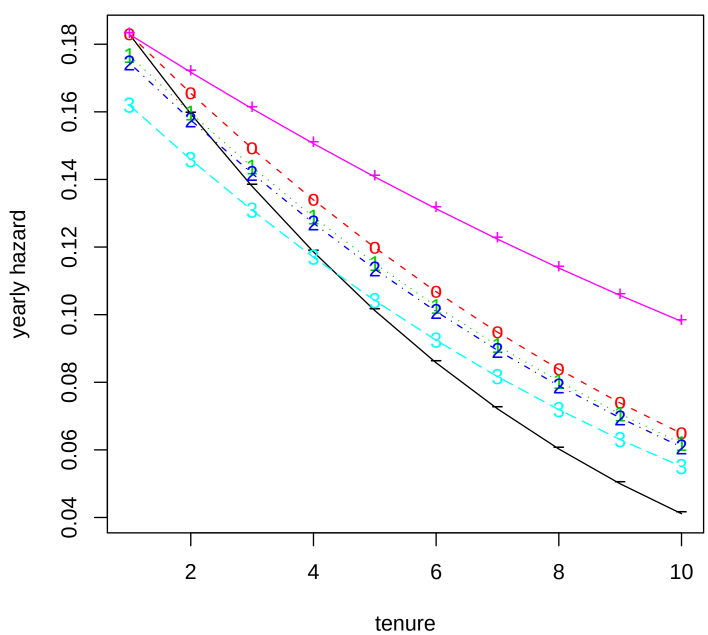

FIG. 4.14 – Counterfactual hazards of quitting self-employment for a probit model

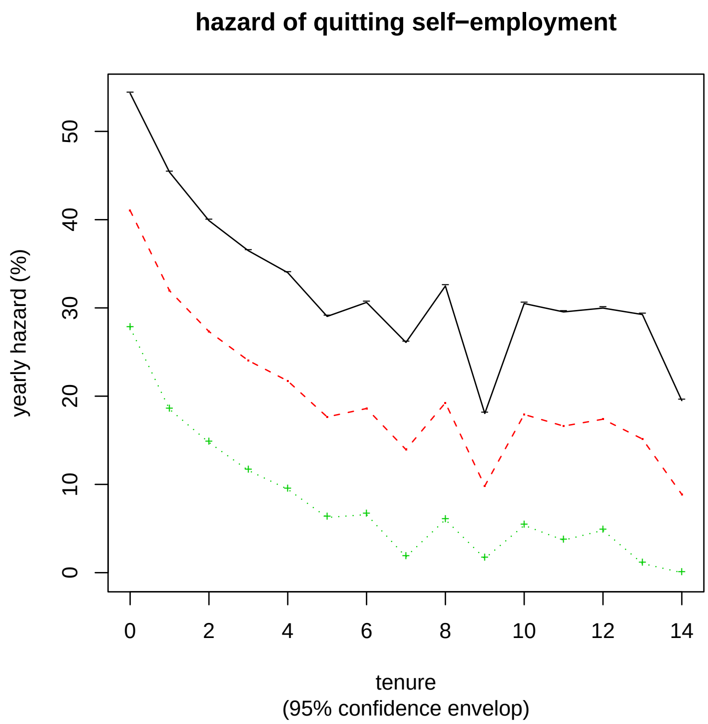

FIG. 4.15 – Baseline hazard of quitting self-employment for a probit model controlling for time varying tenure effect

Chapitre 5

A Dynamic, Structural, Empirical Model of Entrepreneurship

5.1 Introduction

This chapter aims at adapting chapter 4 into a structural model. I have seen that self-employment is a significant and diverse phenomenon. I also found out that the dynamic is interesting : some people go to self-employment from employment, others from unemployment. Some are here to stay. The rest returns their original condition after a few months.

On the top of that, this chapter is based on two papers mainly. Eckstein and Wolpin (1989) who model transitions between employment and unemployment jointly with wages, Keane and Wolpin (1997). I build a structural model that encompass the reduced formed I estimated before. Beyond the research questions I raised in the previous chapter, I look to figure out whether the use of of the AMPL one-step methodology simplify the estimation of a given structural model. Unlike chapters 2 and 3, where the structure was reduced to a mere equilibrium equation and the one-step method was a matter of elegance and choice, it may be here a bare necessity as dynamic discrete choice model brings thousands of constraints, through Bellman equations mostly. Henceforth I proceed as follows : I present the model in section 5.2, in section 5.3 I explain how I use the sample I build in the previous chapter, and section 5.4 presents the estimation. A full version of the model is available in Guitard (2008).

5.2 Model

5.2.1 Overview

In this model, I consider individual professional trajectories from the entry into the job market up to mid-career. The model is set in discrete time. The time unit is the year. There are three possible types of occupation : unemployment, wage-earning and self-employment. In the full version of this model - see Guitard (2008)- it is also assumed that wage-earners can change employer or lose their job like Burdett and Coles (2004). However for the estimation in this chapter, I aggregate all contiguous spells of employment into one in this preliminary version as I are not able to track intra-status changes (*e.g* an employee moving in a new job but remaining an employee or an entrepreneur changing his business but remaining an entrepreneur).

When a period starts an individual receives a job offer with an exogenous arrival rate, conditional on her previous job status, her human capital (background,unobserved heterogeneous and experience) and the macro environment. If she was a wage earner in the previous period, she would lose her job with an exogenous probability. Like the job offers, this rate depends on human capital (background,unobserved heterogeneous and experience) and macro environment. In this model I encompass both the job offer and the job loss processus's in one probability.

If she was self-employed, she would go bankrupt with another given probability. At last if one was unemployed or wage-earner, she might be able to set up a business.

As she faces credit constrains, she will need to have more capital than a given threshold. As I do not observe capital directly, her capital is a latent variable depending on accumulated earnings.

5.2.2 Formal presentation

Henceforth i is the index for individuals, t a given year.

Occupation. I denote as s_{it} the current job status : Unemployment, U, wage-earning, W, and self-employment, S.

The aggregate economy The economy is assumed to be trend-stationnary. Guitard (2008) summarized its variations around the long-term growth by a binary Markov chain $G_t \in up = 1, down = -1$. Here, for the sake of simplicty, I substitute a linear time trend to G_t

Human capital I introduce four variables controlling for observed human capital H_i : F_i is a dummy for the job status of the father ($F_i = 1$ iff i's father was an entrepreneur), N_i is a dummy for German nationality at birth,$East_i$ controls for an East-german background. E_i is the educational attainment before joining the job market. These four variables are time-fixed. In other words :

$$H_i = \begin{pmatrix} F_i \\ N_i \\ East_i \\ E_i \end{pmatrix}$$

Let introduce a few accumulation variables now. t is a proxy for age, As for experience and tenure variables, X^W and X^S are the number of year effectively spend as a wage-earner or a self-employed, while T^W and T^S denotes the number of years spent in the current job or venture. In that case the experience in unemployment X_{it}^{U} is $t - X_{it}^{W} - X_{it}^{S}$. Tenure in unemployment T^{U} cannot be deduced from the previous variables and must be defined independently. Information is summarized by the vector $\mathcal{X}_{it}$:

$$\mathcal{X}_{it} = \begin{pmatrix} t \\ X_{it}^{W} \\ X_{it}^{S} \\ T_{it}^{U,W,S} \end{pmatrix}$$

The financial capital variable Let denotes K_{it}^{*} the financial capital detained by i. K_{it}^{*} evolves according to :

$$\begin{aligned} K_{it+1}^{*} &= \rho_i K_{it}^{*} + \kappa_i Income_{it} + \epsilon_i^3 \\ \rho_i &= H_i \rho \\ \kappa_i &= H_i \kappa \end{aligned}$$

Unobserved abilities and tastes Taste for leisure, unobserved propensity to catch job offer, unobserved wages or profit premium may enter the Mincer equations and the job transition equations below. Usually encompassed in unobserved fix-effect variable ϵ_i, it consists here of three components. The first control for an unobserved human capital as a a wage-earner, the second for human capital as a business creator and the third as the ability to save. All these may be correlated (positively or not). I assume that taste parameters c^W and c^S are linear combinations of them all.

Utility functions I assume that instant utility is defined as the difference between a log-linear function of the yearly income $Income_t$ and the disutility of working - or cost of leisure- c_{it} . Because the self-employed are likely to dedicate more time to their work than the wage-earner, the disutility of working for the former C^S is supposed to be higher than the cost of working for the latter C^W.

$$\begin{aligned} u_{it} &= \log(Income_t) - c_{it} \\ c_{it} &= c^W(\epsilon_i)1_{s_{it}=W} + c^S(\epsilon_i)1_{s_{it}=S} \\ c^S(\epsilon_i) &> c^W(\epsilon_i) \end{aligned}$$

Instant utility of working as a wage-earner I recall the instant utility in the case $s_{it} = W$:

$$u_{it} = \log(w_{it}) - c^W$$

where c^W is the cost of working as a wage-earner -supposedly fixed here and w_{it} is the yearly wage. As I assume that there must not be any discrimination against foreigner and people born in East Germany in wage contract, this wage will depends on education E_i, experience X_{it}^W and X_{it}^S, tenure T_{it}^W, the unobservable human capital specific to wage-earning ϵ_i^1[1] :

$$\log(w_{it}) = \alpha^{W,0} + E_i\alpha^{W,E} + X_{it}^W\alpha^{W,X^W} + X_{it}^S\alpha^{W,X^S} + T_{it}^W\alpha^{W,T^W} + \epsilon_i^1 + \eta_{it}^W$$

where η_{it}^W is an extreme value noise of s.e. σ^S.

Instant utility of working as a self-employed Once again :

$$u_{it} = \log(\pi_{it}) - c^S$$

where c^S is the cost of working as a self-employed -supposedly fixed here and π_{it} is the yearly profits. Unlike the wage-earner case nationality and geographic background may matter positively or negatively. Immigrants may be outsiders and have less

[1] This requires that the employer do observe this human capital and can include it in the labor contract.

customers : in this case they will be earn less. On the contrary they may turn a very cohesive community network into a strong business niche, and thus earn more. In any case I must assume that nationality and east german background matter. Even more obviously father occupation can have an impact. It is well documented fact that having a father self-employed makes a big difference to business ability. I allow for an effect of education, experience and tenure in self-employment but not for an effect of experience and tenure in wage-earning. At last unobserved human capital must be included :

$$\log(\pi_{it}) = \alpha^{S,0} + F_i \alpha^{F,E} + N_i \alpha^{S,N} + East_i \alpha^{S,East} + E_i \alpha^{S,E} + X_{it}^S \alpha^{S,X^S} + T_{it}^S \alpha^{S,T^S} + \epsilon_i^2 + \eta_{it}^S$$

where η_{it}^S is an extreme value noise of s.e. σ^S. To take into account the greater risk undergone by self-employed, I set :

$$\sigma^S > \sigma^W$$

Furthemore a risk premium can be set by :

$$\alpha^{0,S} > \alpha^{0,W}$$

Instant utility to be out of work In the germany, the jobless get 55% for their last wage w_{it}^L[2]. Hence the utility :

$$u_{it} = \log(w_{it}^L) + \log(0.55) + \eta_{it}^u$$

[2]'Reference wages' henceforth

η^U is a small extreme value noise that allows for small incomes : social benefits, asset returns and so on. It is assumed that :

$$\sigma^S > \sigma^W > \sigma^U$$

Employment transition probabilities i knows that at the end of period t she will have a job offer with a probability ρ^U_{Wit} depending on her job status s_{it}, her human background H_i ,her job experience, her age and unobserved ability as a wage-earner. If she is already a wage-earner this means that she keeps her job or gets a new offer :

$$\log(\rho^U_{Wit}) = l^{U,0}_W + H_i l^{U,H}_W + \mathcal{X}_{it} l^{U,\mathcal{X}}_W + G_{it} l^{U,G}_W + \epsilon^1_i l^U$$

$$\log(\rho^W_{Wit}) = l^{W,0}_W + H_i l^{W,H}_W + \mathcal{X}_{it} l^{W,\mathcal{X}}_W + G_{it} l^{W,G}_W + \epsilon^1_i l^W$$

$$\log(\rho^S_{Wit}) = l^{S,0}_W + H_i l^{S,H}_W + \mathcal{X}_{it} l^{S,\mathcal{X}}_W + G_{it} l^{S,G}_W + \epsilon^1_i l^S$$

As it is trickier to take on discrimination when offers are made than when wages are set, I assume that nationality and geographic backrground may have an impact.

Self-employment transition probabilities If i is jobless (resp. wage-earner) she will have a a business idea at the end of period t with probability Λ^U (resp Λ^W). Once she has a business idea, she must meet have enough capital K^*_{it}. The liabilities threshold $\bar{K}$ depends G_{it} and experience variable $\mathcal{X}_{it}$. She leaves business at the end of the period if her profit are below a threshold π or her capital below $\bar{K}$. I sum up these probabilities through three equations, similar to the employment transition probability.

$$\log(\rho^U_{Sit}) = l^{U,0}_S + H_i l^{U,H} + \mathcal{X}_{it} l^{U,\mathcal{X}}_S + G_{it} l^{U,G}_S + \epsilon^2_i l^U$$

$$\log(\rho^W_{Sit}) = l^{W,0}_S + H_i l^{W,H} + \mathcal{X}_{it} l^{W,\mathcal{X}}_S + G_{it} l^{W,G}_S + \epsilon^2_i l^W$$

$$\log(\rho^S_{Sit}) = l^{S,0}_S + H_i l^{S,H} + \mathcal{X}_{it} l^{S,\mathcal{X}}_S + G_{it} l^{S,G}_S + \epsilon^2_i l^S$$

Summary The state space Ω_{it} includes 15 variables eventually :

$$\Omega_{it} = \begin{pmatrix} H_i \\ \mathcal{X}_{it} \\ G_{it} \\ W^L_{it} \\ K^*_{it} \\ \epsilon_i \end{pmatrix}$$

5.2.3 Bellman equations

5.2.3.1 Value functions in $t+1$ as expected in t

Expected Value in t of staying Unemployed in $t+1$ with an income shock η_{it+1} when Unemployed in t Experience a remains unchanged between the two periods :

$$V^U_{it+1}|_{s_{it}=U,\Omega_{it}} = V^U_{it+1}(H_i, \mathcal{X}_{it}, T^U_{it} + 1, W^L_{it}, K^*_{it+1}, \epsilon_i)$$

Expected Value in t of being Employed in $t+1$ with an income shock η_{it+1} when Unemployed in t Experience remains unchanged between the two periods as employment experience and tenure are updated in $t+1$. The reference wages is updated :

$$\log(w^L_{it}) = \alpha^{W,0} + H_i \alpha^{W,H} + X^W_{it} \alpha^{W,X^W} + X^S_{it} \alpha^{W,X^S} + \epsilon^1_i$$

and tenure is reset to 0. Thus :

$$V^W_{it+1}|_{s_{it}=U,\Omega_{it}} = V^W_{it+1}(H_i, \mathcal{X}_{it}, 0, W'^L_{it}, K^*_{it+1}, \epsilon_i)$$

Expected Value in t of being Self-employed in $t+1$ with an income shock η_{it+1} when Unemployed in t Same remarks for the experience and tenure variables :

$$V^S_{it+1}|_{s_{it}=U,\Omega_{it}} = V^S_{it+1}(H_i, \mathcal{X}_{it}, 0, W^L_{it}, K^*_{it+1}, \epsilon_i)$$

Expected Value in t of being Unemployed in $t+1$ an income shock η_{it+1} when Employed in t One more year of job experience is added. Tenure in unemployment is set at 0.

$$V^U_{it+1}|_{s_{it}=W,\Omega_{it}} = V^U_{it+1}(H_i, X^W_{it}+1, X^S_{it}, 0, W^L_{it}, K^*_{it+1}, \epsilon_i)$$

Expected Value in t of staying Employed in $t+1$ an income shock η_{it+1} when Employed in t One more year of job experience and tenure in the job is added. The reference wages is updated :

$$\log(w^L_{it}) = \alpha^{W,0} + H_i\alpha^{W,H} + (X^W_{it}+1)\alpha^{W,X^W} + X^S_{it}\alpha^{W,X^S} + (T^W_{it}+1)\alpha^{W,T} + \epsilon^1_i$$

$$V^W_{it+1}|_{s_{it}=W,\Omega_{it}} = V^W_{it+1}(H_i, X^W_{it}+1, X^S_{it}, T^W_{it}+1, W^L_{it}, K^*_{it+1}, \epsilon_i)$$

Expected Value in t of being Self-employed in $t+1$ an income shock η_{it+1} when Employed in t Job experience rises by one. tenure in self-employment equals to zeros :

$$V^S_{it+1}|_{s_{it}=W,\Omega_{it}} = V^S_{it+1}(H_i, X^W_{it}+1, X^S_{it}, 0, W^L_{it}, K^*_{it+1}, \epsilon_i)$$

Expected Value in t of staying Unemployed in $t+1$ an income shock η_{it+1} when Self-employed in t One more year of self-employment experience is added while tenure in unemployment equals 0.

$$V^{U}_{it+1}|_{s_{it}=W,\Omega_{it}} = V^{U}_{it+1}(H_i, X^{W}_{it}+1, X^{S}_{it}, 0, W^{L}_{it}, K^{*}_{it+1}, \epsilon_i)$$

Expected Value in t of being Employed in $t+1$ an income shock η_{it+1} and a contract $\mathcal{C}'_{it+1}$ when Self-employed in t As previously one more year of self-employment is added. A new contract is drawn and tenure is set to 0.

$$V^{W}_{it+1}|_{s_{it}=W,\Omega_{it}} = V^{W}_{it+1}(H_i, X^{W}_{it}, X^{S}_{it}+1, 0, W^{L}_{it}, K^{*}_{it+1}, \epsilon_i, \mathcal{C}_{it})$$

Expected Value in t of staying Self-employed in $t+1$ an income shock η_{it+1} when Self-employed in t Tenure and self-employment experience are increased by on year :

$$V^{S}_{it+1}|_{s_{it}=W,\Omega_{it}} = V^{S}_{it+1}(H_i, X^{W}_{it}, X^{S}_{it}+1, T^{S}_{it}+1, W^{L}_{it}, K^{*}_{it+1}, \epsilon_i)$$

5.2.3.2 Value functions in t

Value of being Unemployed in t

$$\begin{aligned}
V^{U}_{it} &= \log(w^{L}_{it}) + \log(0.55) + \eta^{u}_{it} \\
&+ \beta(1-\rho^{U}_{Wit})(1-\rho^{U}_{Sit}) E V^{U}_{it+1}|_{s_{it}=U,\Omega_{it}} \\
&+ \beta\rho^{U}_{Wit}(1-\rho^{U}_{Sit}) E \max_{\eta}\left(V^{U}_{it+1}|_{s_{it}=U,\Omega_{it}}, V^{W}_{it+1}|_{s_{it}=U,\Omega_{it}}\right) \\
&+ \beta(1-\rho^{U}_{Wit})\rho^{U}_{Sit} E \max_{\eta}\left(V^{U}_{it+1}|_{s_{it}=U,\Omega_{it}}, V^{S}_{it+1}|_{s_{it}=U,\Omega_{it}}\right) \\
&+ \beta\rho^{U}_{Wit}\rho^{U}_{Sit} E \max_{\eta}\left(V^{U}_{it+1}|_{s_{it}=U,\Omega_{it}}, V^{W}_{it+1}|_{s_{it}=U,\Omega_{it}}, V^{S}_{it+1}|_{s_{it}=U,\Omega_{it}}\right)
\end{aligned}$$

$$\begin{aligned}
V_{it}^{W} &= \alpha^{W,0} + E_i\alpha^{W,E} + X_{it}^{W}\alpha^{W,X^W} + X_{it}^{S}\alpha^{W,X^S} + T_{it}^{W}\alpha^{W,T^W} + \epsilon_i^1 + \kappa_{ic(t)}\eta_{it}^{W} \\
&- c_i^W \\
&+ \beta(1-\rho_{Wit}^{W})(1-\rho_{Sit}^{W})EV_{it+1}^{U}|_{s_{it}=U,\Omega_{it}} \\
&+ \beta\rho_{Wit}^{W}(1-\rho_{Sit}^{W})E\max_{\eta}\left(V_{it+1}^{U}|_{s_{it}=U,\Omega_{it}}, V_{it+1}^{W}|_{s_{it}=U,\Omega_{it}}\right) \\
&+ \beta(1-\rho_{Wit}^{W})\rho_{Sit}^{W}E\max_{\eta}\left(V_{it+1}^{U}|_{s_{it}=U,\Omega_{it}}, V_{it+1}^{S}|_{s_{it}=U,\Omega_{it}}\right) \\
&+ \beta\rho_{Wit}^{W}\rho_{Sit}^{W}E\max_{\eta}\left(V_{it+1}^{U}|_{s_{it}=U,\Omega_{it}}, V_{it+1}^{W}|_{s_{it}=U,\Omega_{it}}, V_{it+1}^{S}|_{s_{it}=U,\Omega_{it}}\right)
\end{aligned}$$

$$\begin{aligned}
V_{it}^{S} &= \alpha^{S,0} + F_i\alpha^{F,E} + N_i\alpha^{S,N} + East_i\alpha^{S,East} + E_i\alpha^{S,E} + X_{it}^{S}\alpha^{S,X^S} + T_{it}^{S}\alpha^{S,T^S} + \epsilon_i^2 + \eta_{it}^{S} \\
&- c_i^S \\
&+ \beta(1-\rho_{Wit}^{S})(1-\rho_{Sit}^{S})EV_{it+1}^{U}|_{s_{it}=U,\Omega_{it}} \\
&+ \beta\rho_{Wit}^{S}(1-\rho_{Sit}^{S})E\max_{\eta}\left(V_{it+1}^{U}|_{s_{it}=U,\Omega_{it}}, V_{it+1}^{W}|_{s_{it}=U,\Omega_{it}}\right) \\
&+ \beta(1-\rho_{Wit}^{S})\rho_{Sit}^{S}E\max_{\eta}\left(V_{it+1}^{U}|_{s_{it}=U,\Omega_{it}}, V_{it+1}^{S}|_{s_{it}=U,\Omega_{it}}\right) \\
&+ \beta\rho_{Wit}^{S}\rho_{Sit}^{S}E\max_{\eta}\left(V_{it+1}^{U}|_{s_{it}=U,\Omega_{it}}, V_{it+1}^{W}|_{s_{it}=U,\Omega_{it}}, V_{it+1}^{S}|_{s_{it}=U,\Omega_{it}}\right)
\end{aligned}$$

Value of being Employed in t

Value of being Self-employed in t

Terminal value. Here I assumes the terminal value is flat.

5.3 Data

The data are essentially the same as in chapter 4 : all the male residents [3] surveyed at least once between 1984 and 2003 and whose age ranges between 16 and 55 at the time they entered the survey are selected in my master sample. Thus I get a wide un-balanced file recording 16678 individuals. Out of them,1984 got self-employed at some point of the survey. They represent $13,9\%$ of the population of interest. In other words there are enough of them to in the master sample to make a valid statistical analysis. Each observation is sample-weighted according to the recommendations of the DIW.

For the memory size constraint in KNITROAMPL I take a random subsample of the latter when I plug my data into the AMPL routine. It is typically made of 550 individuals. This limitation can turn into an advantage as it allows me to do an 'easy-bootstrap' of my estimates and thus to get the variances thereof. Yet I should find out a fix to this practical limitation in future research.

5.4 Estimation

I estimate a simplified version of the model above.

- I calibrate β to 0.8.
- I reduce human capital variables to a dummy 'Father works as an entrepreneur'.
- For the sake of generality I assumes that in ρ_S all covariates maybe active.
- I assimilate the pay-off of unemployment $\log(w_{it}^L) + \log(0.55) + \eta_{it}^u$ to α^U
- I do not observe financial assets K_{it} but dummies for the type of capital owned : K_{it}^{sav}, savings, K_{it}^{lif}, life insurance, K_{it}^{bui}, building contracts, K_{it}^{bnd}, bonds, K_{it}^{phy},

[3] I aggregate samples A,B,C,D,E and F in the GSOEP terminology

entrepreneurship. I make an index out of this four variables[4] and assume it makes a good proxy for the financial capital variable.

– I reduced the unobserved heterogeneity to one discrete component.

These simplifications are mainly due to AMPL technical constraints. As I said above, it is likely that a fix will be found out in the future to allow the estimation of the full version of the model.

The extreme value settings for the η allow me to substitute the $E\max$ operators with the composed operators $\log(\sum(\exp($ in all my computations

The log-likelihood of the problem is not far from a logit setting :

$$
\begin{aligned}
L(\alpha^{U,W,S}, c^{W,S}, \rho_{W,S}^{U,W,S}) &= \Sigma_{iinI}\log(\Sigma_{uinU}p_u\Pi_{tinT}e^{(}V_{it}^{s_{it}}(\Omega_{it}))\\
&* \quad (\frac{(1-\rho_{Wit}^{W})(1-\rho_{Sit}^{W})}{e^{(}V_{it}^{U}(\Omega_{it}))} + \frac{\rho_{Wit}^{W}(1-\rho_{Sit}^{W})}{e^{(}V_{it}^{U}(\Omega_{it})) + e^{(}V_{it}^{W}(\Omega_{it}))}\\
&+ \quad \frac{(1-\rho_{Wit}^{W})\rho_{Sit}^{W}}{e^{(}V_{it}^{U}(\Omega_{it})) + e^{(}V_{it}^{S}(\Omega_{it}))} + \frac{\rho_{Wit}^{W}\rho_{Sit}^{W}}{e^{(}V_{it}^{U}(\Omega_{it})) + e^{(}V_{it}^{W}(\Omega_{it})) + e^{(}V_{it}^{S}(\Omega_{it}))}))\\
&+ \quad \Sigma_{iinI}\log(\Sigma_{uinU}p_u\Pi_{tinT}1/\sigma_{it}e^{(income_{it}-\alpha^{s_{it}})/\sigma^{s_{it}}} * e^{-e^{(income_{it}-\alpha^{s_{it}})/\sigma^{s_{it}}}})
\end{aligned}
$$

For the sake of tractability I maximize this log-likelihood on the rectangular subsample made of all the individuals with non-missing variables between 1998 and 2003 (included). Thanks to KNITRO-AMPL I write this problem as a maximization under constraints here the previous Bellman equation. I discretize the state space as shown in table 5.1 and I end up with fonction value containg $90,000$ cells. Out

[4] $\left(K_{it}^{sav}, K_{it}^{lif}, K_{it}^{bui}, K_{it}^{bnd}\right)$ is a measure of wealth. Let Z_{it} a L-vector of observed covariates, including past income measures. I estimate a multinomial logit model for $\left(K_{it}^{sav}, K_{it}^{lif}, K_{it}^{bui}, K_{it}^{bnd}\right)$ given Z_{it}. Using $(0,0,0,0)$ as reference category, this yields $2^4 - 1 = 15$ linear indices BZ_{it}, where B is the $15 \times L$ matrix of parameters. The first principal component of $[BZ_{1t}, ..., BZ_{Nt}]$, $\left(\widetilde{K}_{1t}, ..., \widetilde{K}_{Nt}\right)$, is our asset measure :

$$\widetilde{K}_{it} = \phi_0 + \phi_1 K_{it} + \nu_{it},$$

where ν_{it} is some classical measurement error.

Dimension	# of point
Occupation	3
Father independent	2
Experience as wage-earner	5
Experience as self-employed	5
Tenure as wage-earner	5
Tenure as self-employed	5
Financial capital	2
Unobserved Heterogeneity	2
Time Trend	6

TAB. 5.1 – State space discretization

of these cells only those for which experience in an field exceeds tenure thereof are feasible brings active constraints. Moreover a double non-zero tenure (in wage-earning and self-employment) is not feasible. So in practice we end up with 27000 active constraints.

The income parameters α are well-identified by the earning data and show a relatively consistent pattern with the previous literature as shown in Table 5.2. Whether it is statistically consistent with the reduced-form is still to be proved as the standard errors are still fragile and the structural and the reduced-form estimates are not fully comparable. Looking at the intercept we see that there are two types of individuals. The first type has a low frequency ($< 5\%$) and is made of people relatively less well-off whatever their occupation. In this type the expected hierarchy of occupation is respected as the jobless receive less than the wage-earners, who are themselves less well-off than the self-employed of that type. In the second type -the more common-average incomes are much higher and the hierarchy is much flatter. Having a father self-employed has little impact on income except for the jobless, maybe because a self-employed father can help a son with temporary jobs in his firm. Looking at the tenure and experience estimates one can see than one more year of employment brings $12.1\% + 0.16.4\% = 4.3\%$ and one more year of self-employment is even more profitable as it yields $8.1\% + 1.3\% = 9.4\%$. Financial capital has slight negative impact on the income of the self-employed.

The cost of leisure by occupation (employment and self-employment) is available Table 5.3. As ρ they much harder to identify economically at least at this stage. For the ρ it is hard to disentangle whether people are in an occupation because they **chose** it -formally their V drove them into that occupation-or because they were constraint by their opportunity sets -formally the ρ. Even if the algorithm finds a solution, this is maybe only shaped by parametric identification and thus the results below must be taken very cautiously. Still, from the intercept coefficients, one sees that the persistence in an occupation is high : wage-earner tends to stay wage-earner over years and the same for the self-employed. Financial capital seems to have slightly negative impact of getting job or business opportunities. Having a father self-employed seems to help a bit to stay in business when one is already self-employed.

The function values show nicer patterns. Number of cells for which self-employment is a better option than wage-earning slightly exceed the number of cells for which wage-earning is better. This number **increases** by 12% when one goes from low financial capital levels to high financial capital levels, by 5% when one goes from a

	α^U	α^W	α^S
Father	1.4	-0.103	0.05
independent	0.217	0.102	0.003
Experience	-0.224	-0.121	-0.131
as wage-earner	0.041	0.332	0.014
Experience	0.192	0.074	0.081
as self-employed	<0.001	0.04	0.032
Tenure	-	0.164	0.013
in the current position		0.746	0.04
Financial	-0.183	0.025	-0.028
capital	0.702	0.291	0.338
Time Trend	-0.140	0.012	-0.036
	0.684	0.069	0.006
Intercept	6.567	7.141	8.7754
(Type 1)	0.822	0.015	0.607
Intercept	10.425	10.253	10.7118
	1.416	0.851	0.069
σ	1.773	0.640	0.560
N.OBS	531	531	531

TAB. 5.2 – The income structure by occupation (s.d below estimates)

always-wage-earner father to a father self-employed at least once. Please note that all these numbers are in cells and not in observed frequency.

c^U	c^W	c^S
0	≈ 3	≈ 5

TAB. 5.3 – The cost of leisure (instable at this stage))

$p_{Type=1}$	$p_{Type=2}$
0.039	0.961

TAB. 5.4 – The unobserved type distributions (2 types)

	ρ_W^U	ρ_W^W	ρ_W^S	ρ_S^U	ρ_S^W	ρ_S^S
Father independent	-0,2	-0,75	-0,3	-0,1	-0,100	0,8
Experience as wage-earner	0,100	-0,700	0,000	0	0,200	-0,1
Experience as self-employed	1,000	-1,400	0,200	0	0,200	-0,6
Tenure	-	-0,2	0,1	-	-0,400	-0,2
Financial capital	-0,100	0,500	0,000	-0,2	0,500	-0,100
Time Trend	OUI	OUI	OUI	OUI	OUI	OUI
Intercept (Type 1)	-2	2	-0,2	-2	-2,000	2
Intercept (Type 2)	-4	2.3	0,2	-2,1	0	2,2
N.OBS	531	531	531	531	531	531

TAB. 5.5 – The opportunity structure by occupation (s.d below estimates)

5.5 Conclusion

This chapter is very incomplete yet. Some limitations due to AMPL technical features must be fixed in the future. The economic identification of V and ρ is still made difficult at this stage as I cannot tell easily people chose or not their occupation. I must also carry out a more complete bootstrap to make my variances robust. Hence, I will be able to make a proper comparison between the reduced-form estimates of chapter 4 and the structural estimates of this chapter. In a word -as for chapters 2 and 3- indentification, stability an robustness must be examine thoroughly.

Chapitre 6

Conclusion

Les politiques publiques de l'emploi ont engendré une littérature volumineuse ces dernières années. Face à cet enjeu majeur qu'est la réduction du chômage dans nos économies, elle commence seulement à éclairer le débat public, grâce notamment à la diffusion des expériences contrôlées. Mais à peine ces méthodes commencent-elles à être connues du public que deux critiques ou questions se font entendre notamment de la part des praticiens :

- Si les politiques testées ont des effets d'équilibre, les généraliser à un groupe plus large que l'échantillon expérimental risque d'entraîner des effets inattendus, que seule l'écriture d'un modèle explicite permet de scénariser les trajectoires professionnelles.
- Un modèle totalement agnostique permet-il de prévoir l'effet à moyen terme des politiques expérimentée ? Comment extrapoler les conclusions à d'autres groupes que l'échantillon test ?

Dans cette thèse je me suis proposé d'examiner les conséquences de deux de ces limites sur l'évaluation des deux politiques du PARE en France, l'accompagnement et la formation des demandeurs d'emploi et sur un sujet général cher à l'opinion, le travail indépendant. J'ai adopté une stratégie structurelle dans les chapitres 2, 3 et

5. Cette approche structurelle a été abordée comme une extension des évaluations en forme réduite et non comme leur antithèse. Conscient des difficultés d'implémentation, je me suis attaché suivant les recommandations de Judd à simplifier à maximum la mise en oeuvre grâce à l'usage du logiciel AMPL.
D'une façon générale beaucoup de travail reste à faire pour affiner et rendre robustes ces résulats. Les conclusions économiques faites dans chacun des chapitres 2,3 et 5 sont donc à prendre avec prudence et devront être étayées par des recherches futures. Enfin, ne disposant du coût social des mesures étudiées, une analyse coût-bénéfice complète n'a pu être réalisée dans le cadre de cette thèse.

Le chapitre 1 Ce chapitre apporte quelques faits nouveaux.

Tout d'abord, la non prise en compte des effets d'équilibre peuvent induire en erreur le chercheur dans son évaluation de la politique **même quand le groupe de traitement est petit.** Par exemple ici, une évaluation naïve en différences de différences sur le taux de sortie du chômage pousse à conclure que l'accompagnement des demandeurs augmente le taux de sortie moyen (traités et non traités) alors que la conclusion peut être inversée quand l'on tient compte des effets d'équilibre même quand la proportion des traités est faible.
Ensuite, les effets d'équilibre peuvent être non monotones. Dans le cas de l'accompagnement : l'externalité négative sur le taux de sortie moyen du chômage va en s'amplifiant avant d'atteindre un maximum -lorsque le chômage est devenu très dual- puis diminue jusqu'au point où tout le monde est traité instantanément : le chômage est redevenu uniforme.
Troisièmement on voit que ces effets d'équilibre varient beaucoup selon les micro-marchés. Ils sont notamment plus importants pour les travailleurs les plus en marge de l'emploi comme les femmes et les moins qualifiés.
Ces résultats ont aussi des conséquences en terme de politiques publiques. Ils montrent tout d'abord qu'il est important de bien tenir compte des effets d'équilibre dans les

évaluations. Leur impact n'est pas sans nuance : la non-monotonicité de ces effets pour l'accompagnement par exemple rend crédible l'hypothèse selon laquelle il est bénéfique si on l'applique à grande échelle et contre-productive si on se contente de l'appliquer à petite ou moyenne échelle.

Il reste bien sûr beaucoup de questions pour de futures recherches. Le résultat montre une grande hétérogénéité des effets. L'origine de cette hétérogénéité est encore mal comprise. Le contexte institutionnel est aussi très important comme le rapportent de nombreux praticiens des métiers de l'accompagnement. D'un point de vue méthodologique les questions d'identification, de stabilité des algorithmes et de robustesse des estimateurs mériteraient d'être approfondies.

Le chapitre 2 Ce chapitre met en évidence des effets d'équilibre de la formation. Il montre que sur les données de Fichier Historique de l'ANPE, l'effet demande excède les effets d'éviction. La formation augmente le temps moyen d'employabilité des chômeurs faisant ainsi baisser les coûts de vacance : les employeurs sont incités à créer des postes supplémentaires **accessibles à tous -formés ou non-**. Cet effet est apparemment supérieur à l'effet attendu de file d'attente ou d'éviction dans lequel ce sont les chômeurs formés qui bénéficient de cette amélioration aux dépens des chômeurs non formés ou en formation.
Le modèle explique aussi le fort effet lock-in observé pour les chômeurs en formation. Pour eux, quitter la formation signifie renoncer à un allongement moyen des contrats. Une offre reçue en cours de formation doit donc être particulièrement avantageuse -c'est à dire longue dans ce modèle- pour pouvoir les débaucher.
Comme au chapitre précédent les effets d'équilibre sont aussi importants pour l'évaluateur des politiques publiques. Ils modifient sensiblement l'effet direct de la formation à savoir l'allongement moyen des contrats notamment en faisant apparaître une durée de réservation pour les chômeurs formés ou en formation et en modifiant

le taux d'arrivée des offres. Ne pas en tenir compte c'est surestimer l'impact de la formation sur les durées en emploi et sous-estimer son effet sur les taux d'arrivée des offres.

Comme au chapitre 2 il reste beaucoup de questions pour de futures recherches : identification, stabilité et robustesse comme je l'ai mentionné plus haut mais aussi sur les effets de stocks (taux de chômage et d'emploi).

Le chapitre 3 Ce chapitre montre que la formation initiale a un impact sur la création d'entreprise que l'on soit employé ou chômeur même si le contexte familial reste au moins aussi prédominant. L'apprentissage mène sans surprise à fonder des entreprises dans l'artisanat et l'industrie tandis qu'une formation supérieure (technique ou non) conduit vers des activités tertiaires.
On montre aussi que les chômeurs tentent plus souvent de créer leur entreprise que les employés -toutes choses égales par ailleurs-, ce qui est cohérent avec l'idée que l'indépendance peut être une échappatoire à une imperfection du marché du travail.
L'effet de l'éducation semble plus fort pour les activités tertiaires que les activités indépendantes du secteur secondaire.
Concernant la survie des activités des indépendants seule l'ancienneté semble avoir un pouvoir explicatif.
Si l'on interprète ces constatations au pied de la lettre, on sera donc enclin à financer les filières professionnelles supérieures pour favoriser la création d'entreprise.
Ces résultats semblent assez robustes à la spécification mais n'ont en revanche **aucune portée causale ou structurelle**. Le but du chapitre suivant est précisément de les rendre compatibles avec un modèle économique explicite. Hors du cadre de cette thèse une expérimentation sociale serait aussi très intéressante pour mettre à jour des relations causales dans ces estimateurs.

Le chapitre 4 On retrouve une partie des résultats sur la hiérarchie et la structure des revenus par type d'occupation. Ce chapitre est cependant encore très incomplet. L'échantillon du chapitre 4 a été considérablement réduit pour des raisons de faisabilité technique. L'identification simultanée des équations d'opportunité -les fonctions ρ- et de choix -les fonctions valeurs- est encore difficile à ce stade : les résultats que j'obtiens sont peut-être entièrement dus à mes choix de paramétrisation. Un boostrap de plus grande ampleur doit encore être réalisé. A partir de là la cohérence avec les estimateurs du chapitre précédent est à vérifier. D'une manière générale, comme aux chapitres 2 et 3, il reste beaucoup de questions pour de futures recherches : identification du modèle, stabilité de l'algorithme de résolution et robustesse des estimateurs.

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