Transitions between Employment, Unemployment and Entrepreneurial Activities – Evidence from Germany

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"*Full employment does not mean literally no unemployment; that is to say, it does not mean that every man and woman in the country who is fit and free for work is employed productively every day of his or her working life ... Full employment means that unemployment is reduced to short intervals of standing by, with the certainty that very soon one will be wanted in one's old job again or will be wanted in a new job that is within one's powers.*"

William Beveridge

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List of Abbreviations

Methods	
RBM	Rule Based Modeling
ABM	Agent-Based Modeling
MAS	Multi-Agent Systems
ODE	Ordinary Differential Equations
SFA	Stochastic Frontier Analysis
ToE	Timing-of-Events
ATT	Average Treatment Effect of the Treated
MPH	Mixed Proportional Hazard Model
IIA	Independence of Irrelevant Alternatives

Economics & Economic Institutions	
FEA	Federal Employment Agency
GDP	Gross Domestic Product
UB I	Unemployment Benefit I
UB II	Unemployment Benefit II
UI	Unemployment Insurance
UA	Unemployment Assistance
SA	Social Assistance
ALMP	Active Labor Market Policy

Data	
SOEP	SOcioEconomic Panel
BHSP	British Household Survey Panel
PASS	Panel Arbeitsmarkt und Soziale Sicherung
	(engl.: German panel survey ‘Labour Market and Social Security’)
GEM	Global Entrepreneurship Monitor
KfW	Kreditanstalt für Wiederaufbau
PSED	Panel Study of Entrepreneurial Dynamics
NLSY1979	National Longitudinal Survey of the Youth, 1979 cohort
PSID	Panel Study of Income Dynamics

This thesis is dedicated to my children Elsa and Neven...

Chapter 1

Introduction

1.1 Background

This dissertation analyzes the mechanisms behind labor market dynamics from different angles. Entrepreneurship is, as well as an alternative to paid labor, a source of job creation. High rates of nascent entrepreneurship can considerably decrease unemployment if the matching of new jobs and the unemployed is efficient and without large institutional frictions. Low matching-efficiency can be a burden both on the unemployed not able to find a job, and on companies not able to find adequate applicants. Additionally, instruments of active labor market policy can also decrease unemployment if they work as intended, which must be carefully evaluated. Tools to evaluate labor market policies must eventually deal with the large heterogeneity in real world societies concerning individual traits such as education, age, etc. Each of the subsequent sections examines labor market dynamics, in particular in Germany, from one of the mentioned perspectives. Section 1.2 outlines my research contributions to this field.

1.1.1 Dynamics in Labor Market Matching

The transitions between unemployment and employment determine peoples' lives in a society. These transitions are mainly driven by the processes of job finding and separation. The matching process connecting employable persons and vacant job positions is not without frictions. At the individual level, matching unemployed people to job vacancies is, itself, not an instantaneous process: first, workers apply for jobs, thereafter firms select the applicant that seems to best fit the job requirements (Mortensen and Pissarides, (1994), Pissarides, (2000), and Rogerson, Shimer, and Wright, (2005)). This yields a time lag during which unemployment and vacancies co-exist, because unemployed applicants wait for hirings and the position remains unfilled until an applicant eventually accepts a job offer. This frictional unemployment is part of a healthy labor market matching process. When short-term unemployment turns into long-term, the

Beveridge curve — with its negative relationship between vacancy rate and unemployment rate — shifts outwards, indicating an inefficient matching process that may lead to persistent mismatch patterns and unemployment. Potential sources for inefficiencies are asymmetric information about the occupational profile of vacant jobs and potential applicants, or unavailable applicants that are locked-in in training measures.

In search and matching theory, a mathematical matching function embodies this microeconomic interplay between labor demand and labor supply. Vacant jobs are released by entrepreneurs and need to be filled by unemployed workers who are searching for jobs (Pissarides, (2000) and Petrongolo and Pissarides, (2001)). From a macroeconomic perspective, the interactions between firms and workers, and the flows of people between unemployment and employment or out of the labor force are strongly affected by periods of up- and down-turns in the business cycle. The exact reasons for fluctuations in job finding and separation rates still pose puzzles in macroeconomic research of labor market dynamics. Labor market fluctuations, and in particular their magnitudes and autocorrelations after shocks in productivity and separation are still not fully understood today (Shimer, (2005), Mortensen and Nagypal, (2007), Hagedorn and Manovskii, (2008), and Shimer, (2008)). A better replication and, hence, understanding, can be achieved with new analytical models, exploratory methodologies or the work in interdisciplinary teams to adapt promising standard methods from one field to the other.

1.1.2 Impact of Active Labor Market Policies

The incidence of long and persistent unemployment remains one of the major challenges in economic policy. There is large body of literature that documents the negative consequences of unemployment for society and the individual: the economy is undermined by declining human capital, lower wages and increasing governmental expenditures on unemployment and welfare benefits. On the individual level, the long-term unemployed often experience a lower wellbeing and an impairment of mental and physical health (Darity and Goldsmith, (1996) and Browning and Heinesen, (2012)). During the last two decades, many European countries went through a paradigm shift in unemployment policy from welfare towards workfare as a response to high and structural unemployment rates. Training measures, job-search monitoring, and sanctions for noncompliance with job-search requirements have become well-established measured used by Active Labor Market Policies (ALMPs) that aim to shorten periods of unemployment (Calmfors, (1995)). The evaluation of specific instruments of ALMPs regarding the effectiveness in encouraging unemployed people to take up jobs earlier and/or not become locked-in to training measures is highly important, they might turn out to be ambiguous for the heterogeneous group of unemployed (Kluve, (2010)).

In Germany, the focus of this thesis, a major part of the decline in unemployment has been attributed to the reform of active and passive labor market policy in the period 2003–2005. The so called 'Hartz' reform led to a substantial restructuring of the unemployment and social benefit system. Its core was the implementation of an extensive monitoring and sanctioning system that aimed to dramatically increase individual job search activities (Jacobi and Kluve, (2006)). Even though the overall unemployment rate decreased from 11.17% in 2005 to 4.98% in 2014, a high stock of long-term unemployed with 44.66% still remains. To date, sanctions are one of the major instruments to encourage unemployed to search and actively apply for jobs. Existing studies generally confirm sanctions as effective instruments to increase the likelihood of finding a job for recipients of unemployment insurance (Abbring, Berg, and Ours, (2005), Boone et al., (2007), Svarer, (2010), and Arni, Lalive, and Ours, (2013)). However, a continuous evaluation of the effect of sanctions on welfare recipients, specific inflow cohorts or specific groups — e.g. the long-term, elderly, or youth — is required to prevent unintended (side) effects (Berg, Klaauw, and Ours, (2004), Klaauw and Ours, (2013), Schneider, (2010), Boockmann, Thomsen, and Walter, (2014), and Berg, Uhlendorff, and Wolff, (2014)).

1.1.3 Transitioning In and Out of Self-employment

Venture creation with a successful performance implies job creation and a reduction in unemployment. A fruitful entrepreneurship landscape is determined by venture creation, and in particular their establishment and survival. The factors that divide the group of entrepreneurs from the group of (un-)employed are examined by a growing number of empirical and theoretical studies on entrepreneurship. Besides regional factors — such as urbanization and localization economies, regional knowledge creation and public institutions (Audretsch and Fritsch, (1994), Fritsch and Mueller, (2004), Fritsch and Falck, (2007), Fritsch and Mueller, (2007), and Bosma et al., (2008)) — personal traits and individual behavior are found to be highly influential upon the decision to become an entrepreneur and stay in business (Caliendo, Fossen, and Kritikos, (2014), Lazear, (2004), and Zhao and Seibert, (2006)).

Moreover, evidence suggests that the group of self-employed is very heterogeneous. Differences between, for example, female and male entrepreneurs (Minniti and Nardone, (2007), Fossen, (2012), and Koellinger, Minniti, and Schade, (2013)), between necessity and opportunity self-employed (Reynolds et al., (2002), Thurik et al., (2010), Block and Sandner, (2009), Caliendo and Kritikos, (2010), and Fossen and Büttner, (2013)), or between own-account-self-employed and self-employed who become employers and hire other workers (Earle and Sakova, (2000), Millán, Congregado, and Román, (2014), and Mandelman and Montes-Rojas, (2009)) are broadly investigated.

Lately, working as self-employed, either part-time, or with an additional wage job on the side ('hybrid' self-employed) has become popular in Germany (Metzger and Ullrich, (2014)) and Europe (European Commission, (2014), Bosma et al., (2008)). Which personal traits or regional determinants influence this development? What exactly turns an employed worker into a part-time or into a hybrid entrepreneur? Are there other differences in the group of self-employed? From a political perspective, is it of particular interest which factors ensure the success and survival of ventures. This knowledge can help develop and improve start-up programs aimed to support entrepreneurs with the best chances to survive and create employment (Fritsch and Mueller, (2007)).

1.2 Own Contributions

Against this background, I will outline each of the four subsequent chapters and their contribution to the field of labor market economics. Although different in topic and methodological approach, Chapter 2, Chapter 3 and Chapter 4 focus on the German labor market. Chapter 2 explores the *employment-to-entrepreneur transition*: which personal traits and motives turn employed people into successful entrepreneurs? Do part-time and hybrid self-entrepreneurs differ significantly from full-time and exclusive entrepreneurs? Chapter 3 and Chapter 4 focus on the group of unemployed people: which factors affect the *unemployment-to-employment transition*? By contrast, Chapter 5 is a methodological excursion to a novel application of Rule-Based Modeling (RBM) — a subclass of agent-based modeling — in labor economics. Thinking outside the box, the simple rule-based labor market model brings together the *interactions and transitions between employed, unemployed and entrepreneurs*.

The first chapter investigates which personal traits and motives affect the self-selection into part-time or hybrid as well as into full-time or exclusive entrepreneurship. My contribution to the understanding of the motives of nascent entrepreneurship builds upon the very few studies by Wennberg, Folta, and Delmar, (2006), Folta, Delmar, and Wennberg, (2010), Petrova, (2012), Raffiee and Feng, (2014), and Block and Landgraf, (2014). Those aim to explain the entry decisions of nascent entrepreneurs who choose between part-time and full-time self-employment, or between hybrid and exclusive self-employment. My analysis reveals the importance of accounting for possible (re)transitions between the two pairs of subtypes of self-employment in addition to the alternative of exit from self-employment. My findings suggest that people with a low risk propensity benefit from an intermediate step into hybrid entrepreneurship. This intermediate step appears crucial, yielding a higher probability of subsequently switching to exclusive self-employment.

Regarding entrepreneurial survival, full-time and exclusive entrepreneurs with prior part-time or hybrid experience are less likely to fail, as predicted by the framework of a standard logit survival model. In contrast, the multinomial probit approach reveals that ignoring the second choice of a (re-)transition to part-time or hybrid self-employment, overestimates the survival probability. The multinomial probit approach shows that prior experience is associated with a higher probability of a re-transition to part-time or hybrid self-employment. Some estimates of the effect of prior part-time and prior hybrid experience on entrepreneurial failure even turn insignificant.

The next two studies, presented in Chapter 3 and Chapter 4, consider the German labor market after the implementation of the 'Hartz' laws in the period 2003–2005 (Jacobi and Kluve, (2006) and Hujer et al., (2006)).[1] While the first study explores the macroeconomic effect of the reform on the aggregate level, the second investigates the impact on individual transitions from unemployment to both employment and non-employment on the micro level.

The first study, presented in Chapter 3, examines regional matching efficiencies in Germany in the years 1998 to 2008. Based on public administrative data at the regional level of 178 local employment agencies, the estimation of an empirical matching function seeks evidence for the effect of the 'Hartz IV' reform on matching efficiency before and after its implementation in 2005. The focus is on the appropriate modeling of the matching function as a crucial element in examining the power of stocks and flows of unemployed job seekers and vacancies in explaining the hirings. Earlier and recent studies adopt the framework of a Cobb-Douglas production function to estimate the impact of unemployment and vacancy stocks on the unemployment outflow in general or, more specifically, on the outflow to employment (Coles and Smith, (1998), Gregg and Petrongolo, (2005), and Coles and Petrongolo, (2008)). As an alternative to the stock-flow matching function in the framework of a Cobb-Douglas production function, I apply a stochastic frontier approach (Ibourk et al., (2004), Fahr and Sunde, (2009), Hynninen, (2009), Hynninen, Kangasharju, and Pehkonen, (2009), and Němec, (2015)). As a functional framework I choose the translog function to address the interactions of stocks and flows in generating new hirings. Furthermore, the twofold structure of a stochastic frontier allows for a modeling of potential sources expected to induce an increase or decrease in matching efficiency over time and between regions (e.g. 'Hartz

[1] In January 2003 the first two 'Hartz' laws ('Hartz I', 'Hartz II'), in 2004 'Hartz III' and in 2005 the last law 'Hartz IV' came into effect.

IV'). According to the results, 'Hartz IV' has increased the matching efficiency for both specifications. The younger and the long-term unemployed contribute to a significantly higher matching efficiency, which is in line with the aims of the 'Hartz IV' reform.

Chapter 4 is based on joint work with my colleague, Ingrid Hohenleitner. The analysis focuses on recipients of Unemployment Benefit II (UB II) who experience sanctions in Germany. Under 'Hartz IV', the monitoring and sanction system was radically reshaped to lower the persistent stock of unemployed, in particular long-term unemployed. By far the majority of European studies evaluating the effect of sanctions focuses on the recipients of Unemployment Insurance (UI). Compared to welfare recipients – in Germany UB II recipients –, they are, on average, more likely to find a job. For example, a significantly large proportion of welfare recipients is long-term unemployed and/or under 25 years. Moreover, only very few of the studies consider the exit from labor-force as a possible consequence of unemployment benefit or welfare sanctions. In our study, we examine the employment probability of UB II recipients. Using a survey sample of UB II recipients covering the years 2005–2007, we also ask whether the intended positive effect of benefit sanctions on employment entry of UB II recipients also results in unintended and increased incentives to leave the labor market. Controlling for the endogeneity of a sanction enforcement, we employ a mixed proportional hazard model for both destinations. Our findings suggest an increasing impact on the outflow to both employment and non-employment.

The last chapter of this thesis presents a particularly novel approach that illustrates the inter-relations between unemployed, employed and entrepreneurs. We apply Rule-Based Modeling (RBM)[2] to a simple labor market model, consisting of employed, unemployed and entrepreneurs. The interaction between these agents follows both explicit-defined and emergent rules. Our simulation allows us to observe the macro-level-effects that emerge from the micro-level-interactions of the agents. This simple example model aims to illustrate the potential of RBM to replicate the labor market dynamics at the macro level 'emerging' from micro interactions between unemployed, employed and entrepreneurs. Chapter 5 is based on Kühn and Hillmann, (2014) — an introductory work that establishes RBM as an alternative tool in the field of agent-based computational economics (Tesfatsion, (2001), Tesfatsion, (2006a)). We provide a discussion of its advantages and limitations. An implementation of RBM can efficiently describe socio-economic interactions and its computational cost compares favorably to other agent based softwares.

[2]Rule-based modeling originally comes from molecular biology.

Chapter 2

Part-time and Hybrid Entrepreneurship: Survival and Transition to Full-time and Exclusive Self-employment

2.1 Introduction

Entrepreneurship, and the establishment of firms are significant determinants of the economic success of a country or region. Venture creation essentially drives the productivity of an economy as entrepreneurs are involved in both innovation and the creation of new jobs. In fact, entrepreneurship and its private and public support are highly important to the steady growth of an economy. Consequently, it is of great interest to understand the factors behind a fruitful entrepreneurship landscape. A large body of literature investigates the role of personal traits and individual behavior, regional determinants, public institutions, legal and political rules and other factors that presumably influence the decision to become an entrepreneur.

Earlier studies look at what affects the decision to become, to be or remain an entrepreneur who devotes all time to entrepreneurial activities. Given the potential financial risks involved with a full-time start-up, less risk tolerant entrepreneurs tend to build up their businesses from the sideline with a wage job. In that sense, 'part-time' entrepreneurs secure a regular income until they get their business off the ground and then switch to running it 'full-time'. Technically, the problem with the terms 'part-time' and 'full-time' entrepreneur is rooted in their generally imprecise definition. Statistical data on entrepreneurs in Europe only distinguishes between full-time and part-time entrepreneurs with respect to weekly workload, even though some part-time entrepreneurs hold a second job and run a so-called 'hybrid' business. In Germany, 40% (13%) of female (male) entrepreneurs worked part-time, where 15% (35%) had a second job in 2012 (European Commission, (2014)).[1] Compared to women, significantly fewer men

[1] According to European Commission, (2014) in 2012 30% (12%) of women (men) entrepreneurs in EU-28 worked part-time, where 15% (31%) of female (male) part-time entrepreneurs have a second job.

decide to establish a part-time business, however more than twice as many male than female part-time entrepreneurs do so with sideline job(s). The Global Entrepreneurship Monitor (GEM) surveys early stage and established entrepreneurs across the globe and classifies countries mostly according to GDP level and growth rate. The annual issue repeatedly reports considerable differences between the proportions of part-timers on the entire number of entrepreneurs. The proportion of part-time early stage ventures as a proportion of the total number of ventures varies between 10% and 60%. For high-income countries, however, the average proportion is nearly 30%, headed by Scandinavia, the Netherlands and Japan, where near half of all early-stage businesses are run in part-time (Bosma et al., (2008), Minniti, Bygrave, and Autio, (2006)).

For Germany, the focus of this study, the annual statistics of the KfW start-up monitor reveal a revival in start-up activity: Compared to 2012, the total number of new enterprises increased by 12%.[2] Specifically, the number of part-time entrepreneurs significantly increased by 22% in 2013, whereas the number of full-time entrepreneurs fell by 3%. Notably 59% of all new ventures are launched with second jobs on the side. (Metzger and Ullrich, (2014)). Furthermore, more women consider self-employment from the sideline. In 2013 roughly 43% of all start-ups had been launched by women, entailing an equal distribution of new businesses between men and women. However, the share of female full-time entrepreneurs on the total number of full-time businesses is only nearly 33%.[3]

Studies by Wennberg, Folta, and Delmar, (2006), Folta, Delmar, and Wennberg, (2010), Petrova, (2012), Raffiee and Feng, (2014), and Block and Landgraf, (2014) focus on the topic of part-time or hybrid entrepreneurship. These analyses investigate the motives and general characteristics of individuals who decide to launch a business with or without a wage job and in part-time or full-time. In spite of the existing studies, a consistent definition for 'part-time' and 'full-time' self-employment is still missing.

Using the German Socio-Economic Panel (SOEP) for the years 2002 to 2012, this paper presents the first longitudinal study, revisiting key drivers that affect individuals' decision to enter part-time, full-time, hybrid or exclusive self-employment. Henceforth, I will distinguish between two pairs of entrepreneurial modes: *part-time* and *full-time* as the first pairs, and *hybrid* and *exclusive* self-employment as the second pair. Recent literature set up two definitions regarding the two entrepreneurial pairs: *Part-time (full-time)* self-employed report a part-time (full-time) workload (Wennberg, Folta, and Delmar, (2006) and Petrova, (2012)). *Hybrid (exclusive)* entrepreneurs obtain income

[2] The KfW Start-up Monitor is a representative annual population survey of start-up activity in Germany provided by the KfW banking group.

[3] Respondents of the KfW survey self-classify their venture into part-time or full-time, mostly according to the weekly workload they contribute to venture activities.

from a wage job and self-employment (exclusively from self-employment) independent of the weekly workload (Folta, Delmar, and Wennberg, (2010), Raffiee and Feng, (2014), and Block and Landgraf, (2014)) (see 2.2.1). Following Block and Landgraf, (2014) and Raffiee and Feng, (2014), I provide new insight into the factors that shape the transition between hybrid and exclusive self-employment, and part-time and full-time self-employment and the survival in each of the four entrepreneurial modes. Besides risk propensity and dual job-holding, I focus on the impact of parental role models and gender aspects on entry, inner-transition decisions and self-employment survival.

The remainder of this paper is organized as follows: Section 2.2 reviews previous research on part-time and hybrid self-employment and the transition between full-time self-employment and the two alternative types of self-employment. Theory and hypotheses regarding the impact of key factors on the entry and transition probabilities are presented in Section 2.3. The description of the estimation sample and variables used in the analysis are given in Section 2.4. The results of the multinomial probit specifications of self-employment entry are presented in Section 2.5, and the results of survival and transition probabilities are shown in Section 2.6. Discussion and conclusion follow in Section 2.7 and Section 2.8.

2.2 Research on Part-time and Hybrid Entrepreneurship

2.2.1 Terms and Definitions

First, it should be emphasized that throughout international and national reports and scientific analyses there is neither an uniform nor consistently applied term nor a definition of part-time and hybrid entrepreneurship. Second, part-time may suggest self-employed work with a reduced weekly workload (Wennberg, Folta, and Delmar, (2006) and Petrova, (2012)), but in other studies it also comprises types of self-employed that are hybrids: self-employed with a sideline wage job independent from weekly workload attributed to either of the two activities (Folta, Delmar, and Wennberg, (2010), Block and Landgraf, (2014), and Raffiee and Feng, (2014)).

Occasionally, GEM informs about the type of entrepreneurs with respect to both working status and amount of time involved in the venture. The GEM classifies part-time and full-time entrepreneurs according to their indicated working hours. In 2007 around 30% of early stage entrepreneurs indicated that they work part-time, whereas the rate differs extensively across countries (Bosma et al., (2008)). In 2005, the majority of early stage businesses were run in full-time (Minniti, Bygrave, and Autio, (2006)), however it is not specified how many of them were run with a side job. For Germany, the KfW startup survey allows respondents to self-classify as a part-time or full-time self-employed. The reports show that the weekly workload appears to determine whether a business is classified as 'part-time' or 'full-time'.

In this study, I propose two definitions for the two types of self-employment: (a) part-time vs. full-time based on weekly workload, and (b) hybrid vs. exclusive based on the income composition. Under (a) self-employed are classified as full-time if they work at least 35 hours per week, whereas under (b) self-employed are referred to as hybrid (exclusive) if they obtain a salaried income and an income from self-employment (exclusively from self-employment).

2.2.2 Literature Review

Empirical evidence on entering full-time self-employment via the hybrid model is scarce and mainly due to lack of data that limits the analysis of the determinants that potentially affect self-employment entry decisions. Wennberg, Folta, and Delmar, (2006) primarily investigate the importance of a sound distinction between part-time and full-time business using the 1997 cohort of the full population of employees in the Swedish knowledge-intensive sector. They estimate two multinomial logit models of transitions: first, the transition into part-time or full-time (or remaining employed) in 1999, and second, for the part-time entrepreneurs, the likelihood of transition to full-time self-employment in 1999.[4] The results strongly support the difference between the effects of uncertainty on the entry to part-time and full-time self-employment and that prior part-time experience impacts the step into full-time positively, interpreting part-time self-employment as an instrument to test the long-run performance of the business strategy.

Folta, Delmar, and Wennberg, (2010) postulate and validate empirically the hypothesis that hybrid self-employment is endogenous to full-time self-employment and must be treated as a distinct process of entrepreneurial entry. Applying a multinomial logit model to Swedish matched employee-employer data (LOUISE), they find that hybrids that engage in becoming full-time self-employed do so under a greater certainty. In general, Folta, Delmar, and Wennberg, (2010) confirm the results of the study by Wennberg, Folta, and Delmar, (2006), but their data sample features an exact classification of part-time and full-time self-employed as it provides information on the main occupation

[4] Wennberg, Folta, and Delmar, (2006) define part-time and full-time entrepreneurs according to the ratio of income from self-employment to total personal income. In fact, individuals with an entrepreneurial income of less than half (half or more) of their total income are classified as part-time (full-time) self-employed. Individuals with no income from entrepreneurial activities are classified as wage employed.

(employee, solo self-employed, employer) and several side jobs of the employees or already self-employed.[5]

Petrova, (2012) develops an entrepreneurial model under liquidity constraints and tests the derived hypotheses empirically using a multinomial probit approach. Exploiting the first wave of the Panel Study of Entrepreneurial Dynamics (PSED) conducted in 1998, Petrova, (2012) estimates the effect of net income and net wealth on the choice to become an early-stage part-time or full-time entrepreneur.[6] Early stage entrepreneurs that report an amount of weekly working hours of at least 35 hours are treated as full-time entrepreneurs, the remaining part is defined as part-timers. In the end, Petrova, (2012) applies a multinomial probit model on a stock sample of 469 part-timers, 194 full-timers and 368 employees as control group. The main findings suggest that financial resources, namely household net worth and household income, are not statistically significant in explaining either part- or full-time early-stage entrepreneurship, or the amount of working hours spent on a part- or full-time start-up. The study provides the missing evidence for the hypothesis of a financially constrained entrepreneur, concluding that the decision for a part-time entrepreneurial activity is rather affected by a learning-by-doing mindset or testing the own entrepreneurial ability.

Raffiee and Feng, (2014) exploit biennially data waves from 1994 until 2008 of the NLSY1979.[7] The data allows the exact identification of hybrids according to their monthly employment status (jobs in paid employment and self-employed). Applying a continuous competing risk Cox model, Raffiee and Feng, (2014) aim to verify the endogeneity of hybrid to full-time self-employment under the impact of risk and core self-evaluation. Exploring to what extent staged entry affects the survival in full-time self-employment, Raffiee and Feng, (2014) include a binary variable taking the value 1, if the respondent transitioned from hybrid to full-time self-employment. Furthermore, Raffiee and Feng, (2014) estimate how tenure of prior hybrid entrepreneurship facilitates the transition to full-time self-employment.

Going one step further, the study by Block and Landgraf, (2014) aims to understand the motives for hybrid self-employed to opt for exclusive self-employment.[8] In conducting a survey between September 2012 and January 2013, they provided the first

[5] Folta, Delmar, and Wennberg, (2010) classify respondents as employees if their primary occupation is employed; full-time self-employed report self-employment as primary occupation and gain no additional income from wage employment. In contrast, hybrid self-employed still indicate employment as the primary occupation, but the total income contains earnings from self-employment already.

[6] The PSED is a nationally representative survey of the establishment of new ventures in the U.S. economy for the purpose of following and analyzing the behavior and decisions made by nascent entrepreneurs and start-ups.

[7] The National Longitudinal Survey of the Youth is a nationally representative sample of 12686 individuals between 14 and 22 years old when the first wave were conducted in 1979.

[8] Block and Landgraf, (2014) use the terms part-time and full-time self-employment instead of hybrid and exclusive self-employment.

insight into transition behavior from hybrid to exclusive entrepreneurship in Germany. From a total of 1199 survey participants they define a sample of 379 current hybrid entrepreneurs, 82 exclusive entrepreneurs who already transitioned from hybrid and 20 former hybrid entrepreneurs who dropped the entrepreneurial career. As with the analysis by Petrova, (2012), also Block and Landgraf, (2014) exploit a stock sample, implying empirical evidence for being transitioned to exclusive self-employment but without information regarding the impact of given factors on the decision to start either of the two entrepreneurial types in Germany.

2.3 Theory and Hypotheses

By intuition and conventional wisdom, there are plenty of reasons to approach full-time and exclusive self-employment out of part-time self-employment with a lower workload or out of a hybrid mode in combination with a wage job. Nascent entrepreneurs may follow the intrinsic motivation of a hobby, aiming to establish it as a professional business project but lacking the required knowledge of how to target and run a business successfully. Remaining in a wage job provides flexible work schedules to pursue an individual business strategy and test it in a hybrid mode with presumably lower risk, and the secure wage job may at least partially offset investment losses if the business strategy turns out to be non-profitable in the long-run. Moreover, a job in an external start-up may provide insights into strategy and potential obstacles of the business formation process and help them become confident in launching their own business and suitably prepared for doing it exclusively. Alternatively, family and/or a lower risk propensity may be reasons to launch a start-up in part-time with a low workload. In the following subsections 2.3.1–2.3.4, I will formulate hypotheses on the impact of risk, dual job-holding, gender and parental self-employment on the entry, transition and exit decisions.

2.3.1 Risk

According to entrepreneurial theory and empirical evidence, one major factor for selection into the group of potential entrepreneurs or potential employees is attributed to the attitude towards risk. Knight, (1921) formalizes an entrepreneurial model under uncertainty allocating less risk averse individuals to labor demanding entrepreneurs and more risk averse individuals to labor supplying workers. Building upon Knight, (1921), Kihlstrom and Laffont, (1979) develop a general equilibrium model of firm formation and survival based on risk aversion. The model by Kihlstrom and Laffont,

(1979) proves that less risk averse individuals become entrepreneurs, whereas more risk averse individuals choose paid employment.

In recent years, empirical work has linked risk propensity to self-employment entry and survival, and has shown, in particular, that self-employed individuals are characterized by higher levels of risk propensity (Cramer et al., (2002), Van Praag and Cramer, (2001), Hartog, Carbonell, and Jonker, (2002)). For Germany, Caliendo, Fossen, and Kritikos, (2009), Caliendo, Fossen, and Kritikos, (2010), Caliendo, Fossen, and Kritikos, (2014) and Biemann and Nieß, (2014) provide profound evidence of the positive role of risk propensity in the decision process to become and stay self-employed. Exploiting SOEP data, they find an inverted U-shaped influence of risk propensity on self-employment survival. However, all these survey studies take the self-report of the self-employment status as major occupation as an indicator for self-employment regardless of what share of working time respondents allocate to their own business. Block and Landgraf, (2014) explore the link between risk propensity and the likelihood of a transition from hybrid to full-time self-employment using a (cross-sectional) survey stock sample of entrepreneurs and therefore lacks longitudinal evidence for the impact of risk on the decision of employees to enter hybrid or full-time self-employment in Germany. Based on these previous results, I will derive the following Hypotheses 1a–1d on entering a specific form of self-employment:

H1a: Risk propensity has a strong positive effect on the likelihood to enter full-time and exclusive self-employment.

H1b: Although risk propensity still affects entry to hybrid self-employment positively, the significance and size of its impact declines.

H1c: Risk propensity increases the probability for an entry to hybrid self-employment only at very high risk propensity levels.

Hybrid self-employment is defined as a mixture of income from risky self-employment and secure wage employment, where the workload is not decisive for classification. The definition of part-time self-employment is independent of income composition but subject to the workload level individuals devote to self-employment activities. On the one hand, individuals decide to launch business in part-time to limit risk in terms of wealth and time invested in self-employment. On the other hand, they likely do so under strict preferences for a reduced amount of weekly working hours and therefore rather independently of their risk propensity, yielding Hypothesis 1d:

H1d: The impact of risk propensity on the entry to part-time self-employment is ambiguous.

The following Hypotheses 1e–1g are formulated regarding the survival and the transition probabilities. After the decision to enter the market as risky full-time entrepreneur, risk is supposed to be a negligible factor for a reverse transition from full-time to part-time or hybrid mode. Hypothesis 1e therefore reads:

H1e: The decision to switch from full-time to part-time, or from exclusive to hybrid self-employment is not affected by risk propensity.

The transition from hybrid to full-time self-employment appears a little differently: Choosing staged entry as the path to full-time or exclusive self-employment through the intermediate step of part-time or hybrid self-employment, appears as a reasonable way to reduce or resolve uncertainty. Hypothesis 1f should apply:

H1f: The impact of risk propensity on the likelihood of a transition from hybrid to exclusive self-employment appears inverted U-shaped, reaching the highest probability for medium risk tolerant hybrid entrepreneurs.

Using SOEP data, Caliendo, Fossen, and Kritikos, (2010), and most recently Biemann and Nieß, (2014), find an (inverted) U-shaped influence of risk on failure (survival) probability but without the distinction between part-time and full-time, or between hybrid and exclusive entrepreneurship. A recent study by Hvide and Panos, (2014) finds that less risk averse individuals are more likely to start a business, but in turn are more likely to perform worse. I posit Hypothesis 1g:

H1g: There is an (inverted) U-shaped relationship between risk propensity and the survival as an entrepreneur: individuals with a medium range of risk propensity are least likely to fail respectively most likely to survive self-employment.

2.3.2 Dual Job-holding

There is a large number of studies exploring the patterns of multiple job holding and the reasons behind them. Previous research agrees on two main motives for holding multiple jobs: the 'hours constrained' and the 'job portfolio' motives. In the framework of the former, the workload of the primary job is limited by a fixed-hours-and-wage-package that, however, falls short of the workers' utility-maximizing income level. Consequently, the worker choose to 'moonlight', thus she holds two or more jobs to increase earnings up to the desired level (Kimmel and Smith Conway, (2001)). The 'job portfolio' motive argues that workers experience an increase in utility if they allocate their working time between two or more different jobs not because they aim to supplement income — instead, they want to gain more work experience, explore other occupational fields or simply obtain flexible work schedules. Using Data from the Panel Study of Income Dynamics (PSID), Allen, (1998) presents first evidence that unconstrained unmarried workers are more likely to 'moonlight' than constrained workers, followed by works of Kimmel and Smith Conway, (2001) and Renna, (2006) that confirm the 'job portfolio' motive. Also, dual or even multiple jobs enable workers to discover new career opportunities and may replace the present primary job with the second job gradually. In particular, Panos, Pouliakas, and Zangelidis, (2014) focus on the dynamics between the primary and the secondary job. Exploiting a sample of the British Household Panel Survey (BHPS), their findings suggest that dual job-holding facilitates job transition and appears as a stepping stone towards self-employment. This motivates the Hypotheses 2a and 2b:

H2a: Second jobs exhibit a positive impact on the probability of entering self-employment.

H2b: Particularly risk-averse people holding a second job have a higher probability of entering full-time or exclusive self-employment.

Panos, Pouliakas, and Zangelidis, (2014) emphasize the role of dual job-holding as one decisive driver towards self-employment. I investigate the impact of dual job-holding in transitions between different types of self-employment. I suppose that for a group of individuals, dual-job holding provides substantial freedom and work flexibility, enabling the development of their own business ideas and strategies to implement in the market. Therefore Hypothesis 2c should apply:

H2c: The likelihood of transition from part-time to full-time self-employment is unaffected by dual job-holding.

Again, second jobs provide a useful tool to become an entrepreneur on-the-job. Multiple job-holding enables flexible work schedules, the learning-by-doing possibility as an employee in small start-ups, or the chance to gain experience in a different work field that is new and appears as a fruitful and more fulfilling career opportunity. Focusing on the survival in hybrid self-employment, (to continue with) second jobs becomes counterproductive. I formulate Hypothesis 2d:

H2d: For hybrid entrepreneurs, second jobs exhibit a negative impact on the likelihood of a transition to exclusive entrepreneurship.

2.3.3 Gender

Then and now, start-ups are dominated by men. In nearly all European countries, most of the existing businesses are owned by men and, still, most of the new ventures are launched by men (Singer, Amoros, and Moska, (2014)). In Germany, the average start-up rate of male entrepreneurs is with 6.5% about 62.5% higher than that of female entrepreneurs (Singer, Amoros, and Moska, (2014), Brixy, Sternberg, and Vorderwülbecke, (2015)). Koellinger, Minniti, and Schade, (2013) explain the gender gap in start-up rates with womens' lack of confidence in their ability to manage a business. The results suggest that men and women differ in the perception of their own skills and entrepreneurial chances. Apart from their subjective perceptions, they possess objective differences regarding their skills and their social and economic situation. Fossen, (2012) investigates gender differences in entrepreneurial choice, presumably affected by risk aversion in Germany. Based on their estimates of the parameter of relative risk aversion within a structural microeconometric model, they find that womens' attitude towards risk merely explains the lower entry rate to self-employment. However, the lower survival rate of female businesses can be evidently explained, to a larger extent, by gender differentials subject to risk aversion. Regarding the four entrepreneurial types, I propose Hypothesis 3a:

H3a: Women are less likely to start a hybrid, full-time or exclusive business than men.

To my knowledge, recent research on gender differentials does not make a distinction between specific types of self-employed people. Apart from the choice between hybrid and exclusive self-employment, the motives to run a business in part-time or full-time differ across specific socio-economic factors. Still, the choice of a part-time business appears rather likely for women as it offers an attractive alternative to attain a flexible work schedule to combine with child care and family, hence Hypothesis 3b should apply:

H3b: The negative impact of being female on the entry decision to hybrid or full-time self-employment turns positive or is offset upon the choice of part-time self-employment.

Looking at the transition and survival probabilities, the same arguments apply, yielding Hypothesis 3c:

H3c: Female exclusive or full-time entrepreneurs are, compared to males, more likely to switch to hybrid or part-time self-employment.

2.3.4 Parental Role Models

It is fairly established that children from self-employed parents per se have an advantage in launching a business and performing successfully (Dunn and Holtz-Eakin, (2000), Bosma et al., (2012)). In following their role model, they gain from the knowledge, experience, social and professional network of their self-employed parents.[9] Most recently, a study by Lindquist, Sol, and Praag, (2015) examines Swedish data and finds that parental entrepreneurship experience increases children's probability to become self-employed by 60%. Studies of part-time and hybrid entrepreneurship, so far considered, generally confirm these findings.

Regarding the literature on part-time and hybrid entrepreneurship, Wennberg, Folta, and Delmar, (2006) and Raffiee and Feng, (2014) leave the influence of parental self-employment unconsidered. Applying a multinomial logit framework, Folta, Delmar, and Wennberg, (2010) reveal that the likelihood of full-time and hybrid self-employment increases significantly if parents of the entrepreneur were self-employed during their childhood. By contrast, Petrova, (2012) employs a multinomial probit model and finds no statistically significant effect of (either) parents business ownership during childhood on the entry to part-time or full-time self-employment.

The estimates of binary logit models of a transition from hybrid to full-time self-employment in Block and Landgraf, (2014) do not support the hypothesis of motivation through role models or tradition significantly.[10] The results imply that, once self-employed, the transitions between the different types (part-time $\leftrightarrow$ full-time or hybrid $\leftrightarrow$ exclusive) and business survival is not significantly affected by self-employed parents. Therefore, I formulate the Hypotheses 4a and 4b:

H4a: The entry probability is positively correlated with parental self-employment

H4b: The likelihood of a transition between the types of self-employment and self-employment survival is not affected by parental role models.

I will test these hypotheses using the data described in the following section 2.4.

2.4 Data

The German Socio-Economic Panel (SOEP) is a representative and remarkably large household panel (Wagner, Frick, and Schupp, (2007)).[11] Using SOEP data, I present a first approach to investigate the impact of individual characteristics on the decision to

[9] SOEP respondents are asked if their parents had been self-employed when they were 15 years old.

[10] The study by Block and Landgraf, (2014) estimates the motive of a general 'role model' as the mean of the level of agreement towards two statements ((a)"to continue a family tradition" and (b) "to follow the example of a person I admire") on the transition behavior of part-time self-employed.

[11] The first SOEP wave was conducted in 1984 as a survey of private households and persons in West Germany. It was substantially enlarged in 2000 with almost twice the number of surveyed persons in 1999. On average, the SOEP covers socio-economic information of nearly 22,000 individuals living in 12,000 households across Germany.

enter self-employment as part-time vs. full-time entrepreneur with either part-time or full-time workload per week, or as a hybrid vs. exclusive entrepreneur with or without a side job.

2.4.1 Estimation Sample

The multinomial probit estimations exploit data of 11 waves of the years 2002 to 2012. The sample is restricted to individuals aged between 18 and 59 years. [12] The full estimation sample is structured into two groups according to the reported primary occupational status: (1) self-employed, where I exclude farmers and self-employed individuals working in the business of a family member as they did not establish the business on their own and (2) wage employed.[13]

The analysis of the choice between part-time and full-time self-employed vs. wage employed, as well as the choice between hybrid and exclusive self-employed vs. wage employed requires two data samples. I classify self-employed individuals as part-time or full-time self-employed in sample A. In sample B, I separate them into hybrid or exclusive self-employed. In either of the two definitions, a primary occupational status of self-employed was reported. The difference between the entrepreneur types in sample A is in the reported workload regardless of whether the self-employed hold job(s) on the side. The SOEP defines individuals as full-time employed if their workload is at least 35 hours per week. For sample B, I refer to income sources to distinguish between hybrid and exclusive self-employed: income from both wage employment and self-employed categorizes respondents as hybrid self-employed, whereas exclusive entrepreneurs obtain income only from self-employed activities.

2.4.2 Explanatory Variables

In the SOEP survey, respondents are asked to indicate their personal willingness to take risks on an 11-point Likert scale ranging from 0 (not willing to take any risks) to 10 (completely willing to take risks). This question was part of the SOEP questionnaire in the years 2004, 2006 and from 2008 until 2012 on a yearly basis. Following

[12] Since 2012, the German official retirement age is in the process of being raised gradually from 65 years to 67 years in 2029. Whereas the realized retirement age for reasons of age has increased steadily from 63 years in 2002 up to 64 years in 2012 (Statistik der Deutschen Rentenversicherung, (2014)), the retirement age for reasons of limited or fully off-set employment decreased on average. However, while the retirement age for employed people generally increases, it drops for individuals who experienced longer periods of unemployment or who have been out of labor market (Bundesministerium für Familie, Senioren, Frauen und Jugend, (2012), Bundesagentur für Arbeit, (2013), Statistisches Bundesamt, (2013)). For clarification, all individuals over the age of 59 count, statistically, as retired.

[13] I exclude self-employed farmers and family members for reasons of a better comparison with existing studies.

Caliendo, Fossen, and Kritikos, (2010), I assume the values of risk propensity (*risk*) of 2004 (2006) to be constant for 2005 (2007). According to Panos, Pouliakas, and Zangelidis, (2014), dual job-holding enables the accumulation of new skills and more work experience which, in turn, acts as a stepping stone towards self-employment, especially for risk averse individuals. Due to spillover effects from dual job-holding and the associated enhanced working expertise on the probability for a job or even occupational change, I include a binary variable *Second* equal to 1 if SOEP respondents indicate the prevalence of a second job in their present career. The impact of gender is reflected by a binary variables equal 1 for female respondents (*female*). The impact of parental role models is captured with the binary variable *parents* , which is equal to 1 if either or both parents were self-employed when the respondent was 15 years old (*parents*) (Acs et al., (2004)). I also include variables that likely affect the entry and transition decisions and operate as controls in measuring the impact of risk, dual job-holding, gender an parental role model. As shown in Table 2.1, the specification comprises socio-economic and demographic factors, such as age, German nationality, migration background and family status (married, divorced) and whether there are children younger than 16 years in the household (*children*). In 2009, 31.4% (32.7%) of business founders were between $25-34$ ($35-44$) years old. For individuals between 44 and 55 years the rate dropped rapidly to 19% (Fritsch, Kritikos, and Rusakova, (2012a) and Fritsch, Kritikos, and Rusakova, (2012b)). I include the square product of age as it appears to have a non-linear concave impact on entry probability for at least full-time and exclusive self-employed (Kautonen, Down, and Minniti, (2014)).

To capture differences subject to human capital, I include binary variables taking the value 1 if the individual has finished high-school (*highschool*), holds an university degree (*university*), holds a degree from a higher technological college (*highertechncol*) and/or is currently in an apprenticeship (*apprenticeship*). General working experience in employment (*exp_empl_10*, in 10 years) and unemployment (*exp_uemp*, in years), and particularly as an employee in small firms (*smallFirm*) or in a managerial position (*manager*) are supposed to increase choice probabilities remarkably (Kim, Aldrich, and Keister, (2006),Mueller, (2006), Parker, (2009)). I add earnings from primary job (*incJob1_1000*) and income from renting and leasing (*incCap_1000*) to capture the impact of financial resources on the entry to part-time/full-time or the entry to hybrid/exclusive self-employment (Evans and Jovanovic, (1989), Evans and Leighton, (1989), Kim, Aldrich, and Keister, (2006)). In one robustness specification I include hybrid intensity as the share of total income that comes from self-employment (*hybIntensity*). All specification are estimated with yearly and regional dummies.

Columns 2 and 3 of Table 2.1 show the differences in means between part-time

TABLE 2.1: Descriptive statistics of sample A and sample B (weighted means)

Variable	Sample A		Sample B	
	part-time	full-time	hybrid	exclusive
continuous				
age (in years)	42.83***	44.86	40.18***	45.13
exp_uemp (in years)	0.863***	0.494	0.799***	0.518
exp_empl_10 (in 10 years)	1.292***	2.042	1.407***	1.981
incCap_1000 (in Thousand)	6.383***	13.03	5.630***	12.68
incJob1_1000 (in Thousand)	1.187+	1.400	12.34	—
hybIntensity	0.488	0.593	5.201	—
risk (0-10)	5.208***	5.543	5.510	5.480
discrete (yes=1)				
Second	0.127***	0.048	0.465	0
female	0.764***	0.284	0.469***	0.354
parents	0.112*	0.128	0.101**	0.128
german	0.936+	0.953	0.920***	0.954
migration	0.129*	0.112	0.171***	0.107
married	0.658	0.656	0.551***	0.670
divorced	0.077***	0.106	0.096	0.102
children	0.524***	0.394	0.440*	0.412
disabled	0.039+	0.025	0.024	0.028
highschool	0.516***	0.434	0.481*	0.445
apprenticeship	0.289***	0.387	0.357	0.371
highertechncol	0.293	0.282	0.259+	0.288
university	0.420*	0.384	0.392	0.391
manager	0.100***	0.167	0.232***	0.146
smallFirm[1]	0.360***	0.586	0.417***	0.567
avg. entry & exit rates				
exit(part-time/hybrid)	0.259		0.234	
exit(full-time)		0.089		0.503
entry(full-time)	0.131		0.106	
entry(part-time)		0.024		0.022
N[1]	1485	6909	914	7383

In the columns for part-time and hybrid self-employed, the signs (***/**/*/+) indicate that the mean of the part-time respective hybrid self-employed is statistically different from the mean of full-time respective exclusive self-employed at the 0.1%/1%/5%/10% level.

[1] For *smallFirm* in sample A, N is 1277 (part-time) and 6487 (full-time). In sample B, N is 852 (hybrid) and 6825 (full-time). Means are weighted by SOEP weights provided by wave 29. By definition of exclusive self-employment in sample B, there are no observations for earnings from primary job *incJob1_1000* and hybrid intensity *hybIntensity*.

and full-time self-employed in sample A, the last two columns show the differences in means between hybrid and exclusive self-employed in sample B. Full-time and exclusive self-employed are less likely to be female. In sample A, 76% (28%) of part-time (full-time) entrepreneurs are female, whereas the average shares of 47% (35%) female hybrid (exclusive) entrepreneurs do not differ strongly in sample B. Surprisingly, although significant, there are no large differences in the average shares of individuals with self-employed parents. Compared to part-time (hybrid) self-employed, full-time (exclusive) self-employed are more likely to be married, experienced less (more) years in unemployment (employment) in the years of their past employment biography, are wealthier (in terms of interests, dividends from assets and renting out), and a higher proportion had been employed in small firms. On average, they are 2 (5) years older than part-time (hybrid) self-employed. As supposed, on average half of the part-time entrepreneurs have children under 16 years, whereas around 40% of both hybrid and exclusive self-employed have children under 16 years in sample B. Compared to sample A, there are only marginal differences in educational means between hybrid and exclusive self-employed in sample B. The part-time entrepreneurs in sample A appear to be on average more risk averse than the full-time entrepreneurs, whereas the difference between hybrid and exclusive entrepreneurs is insignificant.

2.5 Entry Models

For econometrically valid and plausible predictions of multinomial logit models, the assumption of Independence of Irrelevant Alternatives (IIA) in theoretical choice theory must be satisfied (Maddala, (1983)). According to the IIA, the choice between full-time/exclusive self-employment and wage employment remains unchanged, even though the opportunity of part-time/hybrid self-employment enters the choice set. Intuitively, the choice probability changes if the alternative option of part-time/hybrid self-employment becomes available. Also, the transition probability between stay in or leave full-time/exclusive self-employment changes with the option of (re-)entering part-time/hybrid self-employment.

In the final framework of a multinomial probit model, the unordered dependent variable indicates the choice among multiple feasible outcomes. For sample A, I examine the choice between three outcomes: remaining fully employed with a salaried income (=0), entering part-time self-employment (=1) or full-time self-employment (=2). For sample B, the second and third probable outcome changes to: entering hybrid self-employment (=1) or exclusive self-employment (=2) as an alternative to the initial status of wage employment (=0). The marginal effects for a subset of variables of the baseline specification, evaluated at the mean of each explanatory variable in sample A and B are presented in Table 2.2. For the sake of brevity, the entire estimation output of Model I (excluding dual job-holding), Model II including dual job-holding as the baseline specification and Model III controlling for the interaction of dual job-holding and risk propensity are shown in Table A.1 and Table A.3 in the Appendix. In order to compute relative effects, the mean value of the outcome variable is depicted at the bottom of the respective tables. The results depicted in Table 2.2 partially contradict Hypothesis 1a. The multinomial probit model applied to sample A and sample B obtains a significantly negative linear and a significantly positive squared term of risk. This reveals a U-shaped relationship between risk propensity and entry probability to full-time and to exclusive self-employment and does not entirely support Hypothesis 1a. On average, less risk averse individuals enter self-employment, however a marginal proportion of very risk averse and very risk tolerant individuals exhibit an equally high entry probability. The entry rate decreases to the lowest entry probability for medium risk averse individuals and increases subsequently to the highest probability for highly risk tolerant individuals. Excellent business ideas and passion for innovation seem to compensate for a low risk propensity as a factor that affects the entry to full-time and exclusive self-employment negatively.

TABLE 2.2: Entry to part-time/hybrid or full-time/exclusive self-employment

	(1) — Sample A		(2) — Sample B	
	part-time	full-time	hybrid	exclusive
female	0.0001	-0.00207***	-0.00078**	-0.00040*
	(1.12)	(-4.55)	(-1.98)	(-1.65)
parents	0.00021	0.00105	0.00153*	0.00067
	(1.00)	(1.31)	(1.72)	(1.47)
risk	0.00000	-0.00072**	-0.00018	-0.00042***
	(-0.29)	(-2.43)	(-0.61)	(-2.84)
risk_sq	0.00000	0.00014***	0.00008***	0.00006***
	(0.91)	(4.90)	(2.88)	(4.27)
incJob1_1000	-0.00000	-0.00000	-0.00005***	-0.00000
	(-1.12)	(-0.89)	(-2.92)	(-1.23)
incCap_1000	0.00000	0.00002***	0.00001***	0.00001***
	(0.87)	(4.02)	(2.61)	(3.70)
manager	0.00016	0.00535***	0.00255***	0.00300***
	(0.93)	(5.68)	(3.46)	(4.54)
Second	0.00044	0.00222***	0.00509***	0.00070*
	(1.16)	(2.85)	(5.36)	(1.80)
N		88189		88189
mean outcome	0.0024	0.0059	0.0047	0.0036
Log-Lik		-4145.2		-4262.9

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regarding the choice probability of hybrid self-employment, the estimates show a significant and positive squared term of risk propensity, whereas the linear term becomes insignificant. Compared to full-time entry in sample A, no decreasing entry probability for individuals with a moderate respective medium risk propensity can be revealed, suggesting that the salaried income on the side likely offsets the significance of the negative impact of lower risk propensity levels. Coincidentally, individuals with very high risk propensity levels are also very likely to choose hybrid self-employment. Risk propensity exhibits no significant effects on the likelihood to enter part-time self-employment. Taken together, the estimates confirm the Hypotheses H1b and H1c.

The estimates for sample A in Table 2.2 show significantly positive marginal effects for the impact of dual job-holding on the entry probability to full-time self-employment. The marginal effect of 0.22 percentage points for individuals with a second job translates into a relative effect of 37.3% for a given predicted yearly full-time entry rate of 0.59%. Identical to risk propensity, the estimated marginal effect of dual job-holding on the decision to enter part-time self-employment is not significant. Similarly, given a predicted yearly entry rate to hybrid (exclusive) self-employment of 0.47% (0.36%) in sample B, the corresponding relative effect is an 108.3% (19.4%) increase in entry probability. Except for the entry to part-time self-employment, these findings confirm the results from Panos, Pouliakas, and Zangelidis, (2014) and Hypothesis 2a.

The last two columns of Table A.1 show the estimation results of Model III as a re-specification of Model II: I include two variables of an interaction between dual job-holding and risk propensity in linear and squared terms ($Second \times risk$ and $Second \times risk\_sq$) that aims to estimate the supposed risk-alleviating effect of dual job-holding on the entry probability of risk averse individuals (Hypothesis H2b). The inclusion of the two interaction terms yields a negative conditional impact of having a second job on the probability to enter full-time self-employment. This allows a plausible interpretation only for individuals that indicate the lowest risk propensity level (0). The significantly positive interaction term $Second \times risk$ implies an increasing probability to enter full-time self-employment for risk averse people, whereas no dual job-holding decreases entry probability for rather risk averse people. Highly and moderately risk averse people, in particular, benefit from wage jobs through a significantly higher probability to enter full-time self-employment, which supports Hypothesis 2b. Model III in Table A.3, however, shows that the unconditional positive and significant impact of dual job-holding turns into an insignificant conditional impact on entry to both hybrid and exclusive self-employment.

As proposed by Hypothesis 3a, women are less likely to enter hybrid, full-time or exclusive self-employment: The likelihood for an entry to hybrid respectively exclusive self-employment drops on average by 16.6% respectively 11.1%, expressed as relative effects given a yearly entry rate of 0.47% (0.36%). The probability of entering full-time self-employment is about 35.1% lower than for men. Surprisingly, Raffiee and Feng,

(2014) find no significant effect for gender on the likelihood of both hybrid and exclusive self-employment. According to the results of Model I – a specification without controlling for the impact of dual job-holding – in Table A.3 in the Appendix, women have no significantly lower likelihood to enter exclusive self-employment. This negative but insignificant estimate, however, becomes significant in Model II when the effect of dual job-holding enters the specification. Statistical data provided by the European Commission, (2014) indicate that more male than female entrepreneurs hold wage jobs on the side. In that sense, the estimates may imply a lower likelihood to enter full-time self-employment for women with side jobs than for men with side jobs. In line with Hypothesis 3b, the likelihood to enter part-time self-employment remains unaffected by gender. Apart from a distinction between part-time/hybrid and full-time/exclusive self-employment, previous research states a positive impact of parental role models on the decision to enter self-employment. The estimates of the marginal effects, however, primarily contradict Hypothesis 4a as they reveal a positive and significant effect only for the likelihood to enter hybrid self-employment.

The estimated marginal effects of age confirm that the relationship between age and the entry to self-employment is non-linear, concave and follows an inverted U-shaped curve (see Table A.1, Table A.3 in the Appendix). Higher earnings from primary job reduce the likelihood of an entry only to hybrid self-employment , capital assets play a great positive role in the decision to start-up as full-time, hybrid or exclusive business and especially managerial experience facilitates considerably the entry to full-time entrepreneurship by 90.7%, to hybrid entrepreneurship by 54.3% and to exclusive entrepreneurship by 83.3% given the yearly entry rates. (Mueller, (2006), Kim, Aldrich, and Keister, (2006), and Parker, (2009)).

2.5.1 Robustness

For a greater validity, I test the robustness of baseline Model II with respect to selective control variables that might affect the entry probability in a way that turns other effects insignificant or reverses its relation. The results of the three robustness checks [Robust 1, Robust 2, Robust 3] are shown in Table A.2 and Table A.4 in the Appendix. First, I re-estimate Model II with an interaction term for managerial experience collected in a small firm (*manager*×*smallFirm*) and having worked in a small firm (*smallFirm*). Besides advanced education, managerial experience, managing small firms, and being employed in small firms are associated with a considerably higher entrepreneurial entry probability Kim, Aldrich, and Keister, (2006) and Parker, (2009). I include a measure to control for the impact of the intensity of hybrid earnings (*hybIntensity*) – as the ratio between income from self-employment to total income – prior to the step into

TABLE 2.3: Entry to part-time and full-time self-employment, sample A, by gender

	I		II		III	
	part-time	full-time	part-time	full-time	part-time	full-time
female						
parents	0.00008	0.00174***	0.00007	0.00173***	0.00007	0.00171***
	(0.49)	(2.71)	(0.48)	(2.70)	(0.48)	(2.75)
risk	-0.00000	-0.00033	-0.00000	-0.00032	0.00000	-0.00048
	(-0.02)	(-1.09)	(-0.00)	(-1.08)	(0.10)	(-1.57)
risk_sq	0.00000	0.00008**	0.00000	0.00008**	0.00000	0.00008***
	(0.47)	(2.50)	(0.46)	(2.48)	(0.44)	(2.59)
	(0.49)	(5.25)	(0.47)	(5.20)	(0.47)	(5.22)
Second			0.00010	0.00055	0.00011	-0.00718**
			(0.49)	(0.90)	(0.48)	(-2.38)
Second×risk					-0.00001	0.00257**
					(-0.24)	(2.32)
Second×risk_sq					0.00000	-0.00018*
					(0.26)	(-1.89)
N	43863	43863	43863	43863	43863	43863
mean outcome	.0037	.0038	.0037	.0038	.0037	.0038
Log-Lik	-1900.7	-1887.2	-1883.1	-1616.3	-1882.8	-1967.0
male						
parents	0.00000	-0.00025	0.00000	-0.00028	0.00000	-0.00029
	(0.21)	(-0.25)	(0.17)	(-0.28)	(0.16)	(-0.29)
risk	-0.00000	-0.00090*	-0.00000	-0.00089*	-0.00000	-0.00101*
	(-0.18)	(-1.78)	(-0.23)	(-1.78)	(-0.02)	(-1.94)
risk_sq	0.00000	0.00017***	0.00000	0.00016***	0.00000	0.00017***
	(0.57)	(3.74)	(0.58)	(3.70)	(0.45)	(3.76)
Second			0.00003	0.00221***	0.00006	-0.00094
			(1.16)	(2.79)	(1.12)	(-0.19)
Second×risk					-0.00001	0.00114
					(-0.41)	(0.67)
Second×risk					0.00000	-0.00009
					(0.15)	(-0.63)
N	44326	44326	44326	44326	44326	44326
mean outcome	.0013	.0080	.0013	.0080	.0013	.0080
Log-Lik		-2211.8		-2203.4		-2202.7

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

self-employment as the major occupation [Robust 2] (Folta, Delmar, and Wennberg, (2010)). In the end, I apply Model II on a sample extended by individuals with an age between 59 and 64 years [Robust 3]. The estimated marginal effects for the entry probabilities do not considerably change the size and significance of the effect.

Testing the sensitivity with respect to sample population, I merge the classification for part-time with hybrid self-employment, and the classification for full-time

TABLE 2.4: Entry to hybrid and exclusive self-employment, sample B, by gender

	I		II		III	
	hybrid	exclusive	hybrid	exclusive	hybrid	exclusive
female						
parents	0.00240***	0.00042	0.00235***	0.00041	0.00236***	0.00042
	(3.48)	(1.26)	(3.46)	(1.27)	(3.47)	(1.28)
risk	0.00028	-0.00020	0.00028	-0.00019	0.00013	-0.00019
	(0.83)	(-1.39)	(0.85)	(-1.39)	(0.35)	(-1.33)
risk_sq	0.00002	0.00003	0.00002	0.00003	0.00003	0.00003
	(0.72)	(1.55)	(0.68)	(1.55)	(0.93)	(1.49)
Second			0.00203***	0.00044	0.00016	0.00013
			(3.90)	(1.44)	(0.09)	(0.25)
Second×risk					0.00071	0.00005
					(0.89)	(0.21)
Second×risk_sq					-0.00006	0.00000
					(-0.72)	(0.14)
N	43863	43863	43863	43863	43863	43863
mean outcome	.0044	.0030	.0044	.0030	.0044	.0030
Log-Lik	-1897.4	-1886.3	-1885.2	-1620.3	-1880.8	-1960.5
male						
parents	-0.00101	0.00041	-0.00097	0.00040	-0.00098	0.00040
	(-0.92)	(0.85)	(-0.92)	(0.84)	(-0.92)	(0.85)
risk	-0.00065	-0.00037	-0.00065	-0.00037	-0.00075	-0.00036
	(-1.31)	(-1.54)	(-1.37)	(-1.54)	(-1.47)	(-1.43)
risk_sq	0.00013***	0.00006***	0.00013***	0.00006***	0.00013***	0.00006***
	(2.98)	(2.69)	(2.96)	(2.69)	(2.91)	(2.61)
Second			0.00377***	0.00007	0.00192	0.00084
			(5.72)	(0.14)	(0.65)	(0.38)
Second×risk					0.00068	-0.00020
					(0.61)	(-0.24)
Second×risk_sq					-0.00006	0.00001
					(-0.55)	(0.14)
N	44326	44326	44326	44326	44326	44326
mean outcome	.0050	.0042	.0050	.0042	.0050	.0042
Log-Lik	-2321.0	-2304.8	-2304.5	-1927.8	-2299.8	-2412.2

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

with exclusive self-employment, yielding sample C with the distinction between part-time 'hybrids' and full-time 'exclusives'. The number of full-time 'exclusive' self-employed equals the number of exclusive self-employed in sample B, revealing that all entrepreneurs realize their income exclusively from entrepreneurial activities with a full-time workload. The number of hybrid entrepreneurs equals the number in sample B minus the 66 hybrid entrepreneurs that do not work part-time, yielding 914 part-time 'hybrids'. The estimation results for the entry and transition decisions generally do not change, except for the impact of gender on the entry probability to full-time/exclusive self-employment: the negative impact in sample A and in sample B turns insignificant, as shown in Table A.5.

As gender-specific effects play a non-negligible role in entrepreneurial entry, I run the specifications for men and women. The results for the entry to part-time and full-time self-employment are presented in Table 2.3, the results for the entry to hybrid and exclusive self-employment are shown in Table 2.4. Women are more likely to enter full-time and hybrid self-employment if their parents are/were self-employed during childhood. Very surprising is that women only exhibit a significantly increasing impact of risk propensity on the probability of entry to full-time self-employment, whereas for men the typical effect of an increasing entry probability appears. Women who hold a second job and are moderately risk tolerant exhibit the highest entry probability to full-time self-employment.

2.6 Transition Models

2.6.1 Transitions out of Part-time and Hybrid Self-employment

The estimated marginal effects of Model II upon the likelihood of a transition from part-time (hybrid) to full-time (exclusive) self-employment are shown in column 4 and the marginal effects for the likelihood to exit part-time self-employment are given in column 5 of Table 2.5 (Table 2.6).[14]

Table 2.5 indicates that neither the level of risk propensity, the prevalence of a second job nor parental self-employment exhibit a significant effect on the decision of part-time self-employed to run the business with a full-time workload. The likelihood of a transition from part-time to full-time workload for female entrepreneurs, however, do not differ significantly from the likelihood of men. Also, earnings from primary job, capital assets or managerial experience that influence the basic entry decision, do not matter in this transition process. Instead other factors, such as the years of past employment reveal a significant positive impact on the transition to full-time self-employment (see Table A.6 in the Appendix).

Regarding the transition from hybrid to exclusive self-employment, Table 2.6 shows that the U-shaped impact of risk on the entry decision to exclusive self-employment (Table 2.2) changes to an inverted U-shaped impact. Hybrid entrepreneurs with very low or very high levels of risk propensity are less likely, whereas entrepreneurs with medium risk propensity are most likely to switch from hybrid to exclusive self-employment as visualized in Figure A.1 in the Appendix. My findings suggest that, on average, most tolerant entrepreneurs do not exploit hybrid self-employment as a risk alleviating step

[14] A positive marginal effect in the estimation of the exit probability implies a lower probability of survival in the respective entrepreneurial mode.

TABLE 2.5: Multinomial probit model of part-time transitions, sample A

	I		II		III	
	full-time	exit	full-time	exit	full-time	exit
female	-0.01622	0.03500	-0.01568	0.03550	-0.01773	0.03571
	(-0.71)	(1.05)	(-0.69)	(1.07)	(-0.78)	(1.07)
parents	0.00345	-0.01869	0.00328	-0.01926	0.00423	-0.01824
	(0.13)	(-0.47)	(0.12)	(-0.48)	(0.16)	(-0.46)
risk	-0.00602	-0.04806**	-0.00641	-0.04846**	-0.00546	-0.05349**
	(-0.36)	(-2.07)	(-0.39)	(-2.09)	(-0.31)	(-2.14)
risk_sq	0.00183	0.00318	0.00186	0.00321	0.00201	0.00385
	(1.24)	(1.43)	(1.25)	(1.44)	(1.30)	(1.58)
	(1.19)	(1.04)	(1.20)	(1.05)	(1.11)	(1.05)
Second			0.01769	0.01482	0.16122	-0.02997
			(0.61)	(0.35)	(0.63)	(-0.16)
Second×risk					-0.01552	0.03036
					(-0.26)	(0.41)
Second×risk_sq					-0.00059	-0.00405
					(-0.12)	(-0.58)
N	1475	1475	1475	1475	1475	1475
mean outcome	.1426	.2841	.1426	.2841	.1426	.2841
Log-Lik		-1195.8		-1195.4		-1193.1

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.6: Multinomial probit model of hybrid transitions, sample B

	I		II		III	
	exclusive	exit	exclusive	exit	exclusive	exit
female	-0.13409***	0.09339***	-0.13265***	0.09446***	-0.13236***	0.09423***
	(-3.63)	(2.64)	(-3.57)	(2.63)	(-3.56)	(2.62)
parents	-0.03695	-0.00723	-0.01816	-0.00579	-0.01635	-0.00597
	(-0.67)	(-0.15)	(-0.33)	(-0.12)	(-0.29)	(-0.12)
risk	0.07191***	-0.06980***	0.08099***	-0.07051***	0.06629*	-0.06591**
	(2.64)	(-2.74)	(2.96)	(-2.73)	(1.90)	(-2.01)
risk_sq	-0.00471*	0.00579**	-0.00536**	0.00583**	-0.00402	0.00533*
	(-1.86)	(2.47)	(-2.10)	(2.45)	(-1.21)	(1.74)
Second			-0.18173***	-0.01578	-0.27403*	0.01608
			(-4.70)	(-0.44)	(-1.81)	(0.12)
Second×risk					0.04144	-0.01855
					(0.66)	(-0.35)
Second×risk_sq					-0.00376	0.00185
					(-0.64)	(0.37)
N	994	994	994	994	994	994
mean outcome	.5113	.3014	.5113	.3014	.5113	.3014
Log-Lik		-904.9		-882.0		-881.8

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

into exclusive entrepreneurship. So far, in previous research on hybrid entrepreneurship, no evidence has been presented of the non-linear relationship between risk propensity and the likelihood of a transition or an entire failure. Raffiee and Feng, (2014) estimate the impact of risk propensity, only in linear terms, on the entry to hybrid or exclusive self-employment, and on the survival in exclusive self-employment given a prior hybrid experience. In all estimations, risk propensity makes no significant contribution to explain the entry or exit decisions. Hybrid entrepreneurs who hold second jobs are with 18.2 percentage points less likely to become exclusive entrepreneurs. Given the predicted transition rate of 51% per year, the likelihood reduces relatively by 35.5%. Women's likelihood to switch from hybrid to exclusive mode appears to be 25.9% lower than that for men, in relative terms. With respect to parental self-employment, my estimates do not reveal a significant effect on the transition to exclusive self-employment.

2.6.2 Transitions out of Full-time and Exclusive Self-employment

The estimated marginal effects for the multinomial probit model of a transition to part-time or out of self-employment for full-time self-employed are depicted in column 4 and 5 in Table 2.7. Column 4 and 5 in Table 2.8 show the marginal effects of a transition to hybrid or out of exclusive self-employment. Again, a positive estimated marginal effect of the probability to fail full-time or exclusive self-employment implies a lower probability of survival.

TABLE 2.7: Multinomial probit model of full-time transitions, sample A

	I		II		III	
	part-time	exit	part-time	exit	part-time	exit
female	0.02511***	-0.01402	0.02487***	-0.01390	0.02494***	-0.01414
	(5.40)	(-1.41)	(5.36)	(-1.39)	(5.39)	(-1.41)
parents	-0.00432	-0.00927	-0.00433	-0.00923	-0.00418	-0.00956
	(-1.37)	(-0.77)	(-1.38)	(-0.77)	(-1.33)	(-0.79)
risk	0.00265	-0.01311*	0.00267	-0.01313*	0.00228	-0.01115
	(1.15)	(-1.88)	(1.15)	(-1.88)	(0.97)	(-1.55)
risk_sq	-0.00022	0.00135**	-0.00022	0.00135**	-0.00020	0.00117*
	(-1.05)	(2.09)	(-1.06)	(2.09)	(-0.93)	(1.76)
Second			0.00385	-0.00278	-0.01011	0.09482
			(0.71)	(-0.15)	(-1.06)	(0.95)
Second×risk					0.00518	-0.03852
					(0.56)	(-1.20)
Second×risk_sq					-0.00028	0.00354
					(-0.35)	(1.14)
N	7450	7450	7450	7450	7450	7450
mean outcome	.0249	.1610	.0249	.1610	.0249	.1610
Log-Lik		-3768.5		-3768.2		-3766.9

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7 and Table 2.8 reveal that risk propensity affects general survival in full-time self-employment, whereas the transition to part-time or hybrid entrepreneurship tends to be independent of the entrepreneur's attitude towards risk. Consistent with previous research, and as illustrated by Figure A.2, the impact of risk on exclusive and full-time self-employment failure appears as curvilinear in a U-shaped form (Caliendo, Fossen, and Kritikos, (2010), Caliendo, Fossen, and Kritikos, (2012), Hvide and Panos, (2014), and Biemann and Nieß, (2014)). Interestingly, gender plays a role only for

TABLE 2.8: Multinomial probit model of exclusive transitions, sample B

	II	
	hybrid	exit
female	0.00912**	-0.00291
	(2.05)	(-0.29)
parents	-0.00295	-0.00259
	(-0.65)	(-0.20)
risk	-0.00111	-0.01112
	(-0.42)	(-1.54)
risk_sq	0.00010	0.00117*
	(0.41)	(1.73)
N	7943	7943
mean outcome	.0231	.1782
Log-Lik		-4191.5

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. By definition of full-time self-employment in sample B, full-time entrepreneurs do not have income from a side wage job, so *incJob1_1000* is omitted from the model specification. t statistics in parentheses $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the decision of hybrid entrepreneurs to quit business (Table 2.6); quantitatively, the likelihood is about 31.3% lower than for male entrepreneurs given the yearly exit rate of 30.1%, whereas being female significantly facilitates transition from full-time to part-time self-employment (Table 2.7) by 2.5% points and to hybrid self-employment by 0.9% points (Table 2.8), implying a relative impact of 99.9% respectively 34.6%. Dual job-holding is irrelevant in full-time transitions and survival (Table 2.7).

2.6.3 Robustness

I repeat the robustness analysis from subsection 2.5.1 for the transition models The estimates generally remain unchanged. Most notably, the failure of hybrid self-employment appears to be negatively affected by parental self-employment, whereas in sample A and B neither the transition to full-time/exclusive nor survival seems to be driven by parental self-employment (Table A.10).

2.7 Discussion

This study examines the factors that affect the choice to enter self-employment, and whether to do it as a part-time or full-time, or as a hybrid or exclusive entrepreneur, respectively. Using the German Socioeconomic Panel (SOEP), I offer a first attempt at identifying individuals as part-time or full-time entrepreneurs according to their indicated workload or as hybrid or exclusive entrepreneurs according to their indicated sources of income. Based on two definitions, I examine the impact of risk attitude, dual job-holding, parental self-employment and gender on entry, transition and exit decisions. Multinomial probit regressions estimate risk propensity to be U-shaped influential for the decision to enter full-time and exclusive self-employment, which partially verifies Hypothesis 1a. Hybrid entrepreneurship is most likely chosen by individuals with a high level of risk propensity, which confirms Hypothesis 1b. Compared to the entry to full-time or exclusive self-employment, lower levels of risk propensity do not significantly lower the entry probability. Evidence on this kind of exponentially shaped impact of risk propensity on self-employment, however, without distinction between part-time/hybrid and full-time/exclusive, is provided by the earlier studies of Van Praag and Cramer, (2001) and Hartog, Carbonell, and Jonker, (2002)), and most recently by Caliendo, Fossen, and Kritikos, (2014). Compared to the study by Raffiee and Feng, (2014) on entry in hybrid entrepreneurship, risk enters the estimation specifications only in level terms, overlooking the apparent non-linear relationship between risk propensity and entry probability that I find in my model.

As formulated by Hypothesis 3a, full-time, exclusive and hybrid self-employment is less likely chosen by women. Except part-time self-employment, dual job-holding facilitates the decision to enter self-employment. This result supports Hypothesis 2a. Interestingly, parental role models affect the decision to enter hybrid self-employment positively, but is not important for the entry to full-time or exclusive self-employment. This result partially contradicts Hypothesis 4a that proposes a general positive impact on entry probability. Folta, Delmar, and Wennberg, (2010) restrict the analysis to male entrepreneurs and Petrova, (2012) obtains a positive effect of being male for being a part-time and full-time entrepreneur. A little surprisingly, according to Raffiee and Feng, (2014), the effect of gender on entry to hybrid and exclusive self-employment is not significant. In case of parental role models, Folta, Delmar, and Wennberg, (2010) estimate a positive effect for both entry to hybrid and exclusive self-employment, whereas Petrova, (2012) finds no significant evidence. Folta, Delmar, and Wennberg, (2010) investigate how the experience as a hybrid entrepreneur affects the decision to enter exclusive self-employment, and find both the binary variable equal to 1 for hybrid experience and hybrid intensity to be positively significant. Tables A.2 and A.4 confirm the positive effect of hybrid intensity on the transition probability to full-time and exclusive self-employment.

Focusing on the transitions between part-time and full-time, and between hybrid and exclusive self-employment, my results show that entrepreneurs act differently compared to employment-to-self-employment decisions. Block and Landgraf, (2014) analyze the determinants of a sequential transition from hybrid to full-time self-employment. In their study, parental self-employment and gender cannot explain the transition from hybrid to exclusive entrepreneurship. In case of parental self-employment, the result is in line with my findings for part-time and hybrid entrepreneurs and supports Hypothesis 4b. Compared to men, women are less likely to switch from hybrid to exclusive business, and if full-time or exclusively self-employed, women exhibit a higher likelihood to (re-)enter part-time or hybrid self-employment. This confirms Hypothesis 3c. The survival rates as full-time and exclusive entrepreneur, however, cannot be explained by gender. Studies by Caliendo, Fossen, and Kritikos, (2010), Caliendo, Fossen, and Kritikos, (2012) estimate women's likelihood of survival to be lower compared to men. Accounting for multiple choices in a multinomial probit approach, however, vanishes the gender effect on the exit rate. Most notably, the U-shaped impact of risk on the entry to full-time and exclusive self-employment reverses to an inverted U-shaped influence for the transition from hybrid to exclusive self-employment, and loses significance for the decision to switch from self-employment with part-time to full-time workload. These findings support Hypothesis 1e and 1f. Hybrid entrepreneurs with side jobs are less likely to switch to exclusive self-employment. The large impact of dual job-holding on entry probability vanishes for all transitions between the different modes of self-employment, except hybrid entrepreneurs with jobs on the side lower their likelihood of a transition to exclusive self-employment. Both results confirm Hypothesis 2c and 2d.

In order to show the importance of hybrid experience on self-employment survival, Raffiee and Feng, (2014) employ a Cox proportional hazard model of survival in exclusive self-employment with a binary variable equal to 1 if the entrepreneur was hybrid self-employed prior to the transition to exclusive self-employment. Raffiee and Feng, (2014) find no significant effect of risk on business survival probability and estimate male entrepreneurs to be less likely to leave exclusive self-employment than females. Prior engagement and its duration in hybrid self-employment increase the likelihood of business survival. It should be stressed that Raffiee and Feng, (2014) do not clarify whether a transition back to hybrid self-employment counts as a failure. In contrast, I choose to highlight the interplay between failure and reverse transition to hybrid entrepreneurship by means of a multinomial probit framework. Entrepreneurs have the choice to stay or to change their respective entrepreneurial mode or to entirely leave self-employment. Compared to men, women are more likely to transit from full-time to part-time, however, less likely to leave hybrid for exclusive self-employment.

The findings in Tables 2.6 and 2.7 confirm the U-shaped influence of risk propensity on the exit decision of hybrid and full-time entrepreneurs, and hence Hypothesis 1g

(Caliendo, Fossen, and Kritikos, (2009), Caliendo, Fossen, and Kritikos, (2010), Hvide and Panos, (2014)). Table 2.8 illustrates a positive and significant marginal effect of the squared term of risk on the transition out of exclusive self-employment. The probability of failure increases exponentially with increasing levels of risk propensity. Neither parental self-employment, nor dual job-holding turn out to influence failure, and only female hybrid entrepreneurs are more likely to quit self-employment than male hybrid entrepreneurs. Otherwise, gender does not exhibit any impact on business survival.

TABLE 2.9: Full-time transitions and exit with prior part-time mode, sample A

	I		II		III		IV
	part-time	exit	part-time	exit	part-time	exit	exit
Second	0.00475	0.00933	0.00914	0.01133	-0.06240**	0.00472	0.00732
	(0.81)	(0.61)	(1.44)	(0.69)	(-2.54)	(0.28)	(0.54)
prior							
part-time	0.02339***	-0.01804					-0.02787**
	(6.57)	(-1.41)					(-2.33)
female	0.01948***	0.01661*	0.01776***	0.01691*	0.05237**	-0.00245	0.01283
	(4.51)	(1.94)	(3.98)	(1.90)	(2.04)	(-0.24)	(1.61)
parents	-0.00416	-0.02038**	-0.00332	-0.01570	-0.05433*	-0.02248	-0.01893**
	(-1.32)	(-2.20)	(-1.16)	(-1.62)	(-1.76)	(-1.26)	(-2.24)
risk	0.00214	-0.01406***	0.00156	-0.00953*	-0.00258	-0.02595	-0.01317***
	(0.94)	(-2.63)	(0.76)	(-1.73)	(-0.11)	(-1.44)	(-2.74)
risk_sq	-0.00019	0.00148***	-0.00010	0.00097*	-0.00040	0.00282	0.00135***
	(-0.91)	(2.96)	(-0.52)	(1.90)	(-0.18)	(1.45)	(3.03)
N	6891	6891	6356	6356	535	535	6891
outcome	.0269	.0977	.0180	.0977	.1324	.0974	.0976
Log-Lik		-2690.7		-2343.3		-290.8	-2030.2

Marginal effects, evaluated at the means after Multinomial probit model on (I) a sample of full-time entrepreneurs with the dummy *prior part-time* , on (II) [III] a sample of full-time entrepreneurs without [with] prior part-time entrepreneurship experience and (IV) on a binary logit model of business failure with the dummy *prior part-time* on the unrestricted sample of full-time entrepreneurs. t – statistics in parentheses $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For the sake of demonstrating the importance of the multinomial choice approach, I generate a dummy variable for prior part-time (hybrid) self-employment as done by Raffiee and Feng, (2014) and run a multinomial probit on (I) a sample of full-time (exclusive) entrepreneurs with the dummy, (II) [III] a sample of full-time (exclusive) entrepreneurs without [with] prior part-time (hybrid) entrepreneurship and analogous to Raffiee and Feng, (2014) (IV) a binary logit model of failure with the dummy on the unrestricted sample of full-time (exclusive) entrepreneurs. The results for full-time self-employed with prior part-time entrepreneurship and exclusive self-employed with prior hybrid entrepreneurship are presented in Table 2.9 and 2.10, respectively. In line with previous research, and in contrast to Raffiee and Feng, (2014), the binary Model IV applied to sample A and sample B features the U-shaped impact of risk on the exit probability (H1g). The likelihood of an exit from full-time or exclusive self-employment drops if the entrepreneur had self-employed parents and at least one period spent as part-time or hybrid entrepreneur immediately prior to full-time or exclusive self-employment, respectively. Gender, however, lacks significance for prior part-timers, whereas Raffiee and Feng, (2014) estimate a negative effect of being female. Instead, the findings of Model I show that full-time entrepreneurs with prior part-time experience are 2.3% points more likely to re-enter part-time self-employment than those without. Business survival appears to be unaffected by prior experience in part-time entrepreneurship. Applied to sample B, Model I reveals that prior hybrid entrepreneurship increases probability on a re-transition to hybrid self-employment and increases likelihood of a survival in exclusive self-employment (Table 2.10). Most notably, the positive but insignificant effect of being female in Model IV becomes significant in Model I for both re-entry to part-time and exit from full-time self-employment. In sample B, logit Model IV estimates parental self-employment to affect failure probability negatively, whereas the multinomial approach of the same specification obtains no significant impact of parental role models on neither the re-entry to hybrid nor the exit out of exclusive self-employment. Instead, running Model III shows in general that the transition and failure probability of full-time/exclusive entrepreneurs with part-time/hybrid experience remains unaffected by risk propensity and gender. Summing up, to measure the importance of prior part-time or hybrid entrepreneurship in terms of a dummy variable as a stepping stone to full-time or exclusive self-employment by means of a binary logit regression of business survival is likely misleading. As shown, the effect is two-fold: a lower failure rate is assembled by a strongly positive effect on the re-transition to self-employment with part-time workload and an insignificant effect on failure for sample A. For sample B, the prior hybrid entrepreneurs are less likely to fail but face a higher probability to re-enter hybrid entrepreneurship than those without prior hybrid entrepreneurship.

2.8 Conclusion

Risk propensity ((Cramer et al., (2002), Van Praag and Cramer, (2001), Hartog, Carbonell, and Jonker, (2002)), Caliendo, Fossen, and Kritikos, (2009) and Caliendo, Fossen, and Kritikos, (2010)), parental self-employment and gender are proven highly influential factors for the individuals' decision to enter self-employment (Koellinger, Minniti, and Schade, (2013), Fossen, (2012),Dunn and Holtz-Eakin, (2000), Lindquist, Sol, and Praag, (2015)). According to statistical data for Europe, and in particular Germany, the share of part-time and hybrid entrepreneurs on the entire number of entrepreneurs grows steadily (European Commission, 2014; Bosma et al., 2008; Minniti, Bygrave, and Autio, 2006; Metzger and Ullrich, 2014).

TABLE 2.10: Exclusive transitions and exit with prior hybrid mode, sample B

	I		II		III		IV
	hybrid	exit	hybrid	exit	hybrid	exit	exit
prior hybrid	0.01555***	-0.03736***					-0.03851***
	(4.75)	(-4.63)					(-5.15)
female	0.00844**	0.02028**	0.00772*	0.02429**	0.00454	0.01075	0.01787**
	(1.98)	(2.34)	(1.75)	(2.25)	(0.59)	(0.81)	(2.25)
parents	0.00102	-0.01573	0.00151	-0.00650	0.00938	-0.03061*	-0.01540*
	(0.20)	(-1.58)	(0.33)	(-0.53)	(0.60)	(-1.73)	(-1.73)
risk	-0.00123	-0.01178**	-0.00068	-0.01317*	-0.00566	-0.01222	-0.01086**
	(-0.45)	(-2.02)	(-0.23)	(-1.88)	(-1.23)	(-1.28)	(-2.07)
risk_sq	0.00012	0.00118**	0.00004	0.00128*	0.00057	0.00130	0.00108**
	(0.44)	(2.14)	(0.16)	(1.92)	(1.24)	(1.47)	(2.16)
N	7347	7347	5008	5008	2339	2339	7347
outcome	.0249	.1160	.0184	.1288	.0388	.0886	.1158
Log-Lik		-3091.3		-2071.5		-968.2	-2348.8

Marginal effects, evaluated at the means after multinomial probit model on (I) a sample of exclusive entrepreneurs with the dummy *prior hybrid* , on (II) [III] a sample of exclusive entrepreneurs without [with] prior hybrid entrepreneurship experience and (IV) on a binary logit model of business survival with the dummy *prior hybrid* on the unrestricted sample of exclusive entrepreneurs. t – statistics in parentheses $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

There is an upcoming strand of literature that acknowledges the increasing importance of part-time and hybrid entrepreneurs in the economy, respectively. These studies aim to reexamine the impact of key factors concerning the probability of entering part-time respectively hybrid entrepreneurship (Wennberg, Folta, and Delmar, (2006), Folta, Delmar, and Wennberg, (2010), Petrova, (2012), Raffiee and Feng, (2014), Block and Landgraf, (2014)). Raffiee and Feng, (2014) and Block and Landgraf, (2014) investigate further the determinants that affect the probability of a transition from part-time/hybrid to full-time/exclusive self-employment.

My analysis contributes to the strand of research on hybrid entrepreneurship by revisiting the impact of the factors risk, parental self-employment and gender on the probability to enter, transit to or fail a specific type of self-employment. Using the Socioeconomic Panel (SOEP), I classify self-employed individuals into two entrepreneurial pairs. First, the pair of part-time and full-time self-employed is based on the indicated workload of the self-employed SOEP respondents. The selection into either hybrid or exclusive self-employment – as the second pair – is made upon the income sources. Besides income from self-employment, hybrid self-employed obtain income from a wage job on the side, whereas self-employed without a wage job are termed exclusive self-employed.

Modeling the simultaneous entry choice, I apply a multinomial probit model to the SOEP waves of the years 2002 to 2012. The study especially focuses on motives of people who choose part-time (hybrid) over full-time (exclusive) self-employment. Considering a binary variable that controls for the prevalence of side jobs prior to the entry to any of the possible entrepreneurial modes as an explanatory factor for the probability to fail or transiting to an alternative entrepreneurial mode is new in the literature. As hypothesized, dual job-holding facilitates the entry to self-employment, however, the continuation lowers survival and transition probabilities. Interestingly, gender-specific estimates reveal that the positively significant effect of dual job-holding on the entry to exclusive self-employment becomes insignificant for both women and men. With respect to risk propensity, the estimates show a U-shaped impact on the probability to enter or to fail full-time or exclusive self-employment. Gender-specific estimates show that highly risk averse women with a side job have a higher probability to enter full-time self-employment than those without a side job.

The relationship between risk propensity and the probability of entering full-time or exclusive self-employment out of employment follows an U-shaped form: a marginal proportion of very risk averse and very risk tolerant individuals exhibit an equally high entry probability. Regarding the transition from hybrid to exclusive self-employment, my findings suggest that individuals with a moderate risk propensity likely exploit hybrid entrepreneurship as a stepping stone into exclusive self-employment. The inverted U-shaped relationship between risk propensity and survival probability was found only for hybrid and full-time entrepreneurship. The probability of survival in exclusive self-employment is negatively affected only for very high levels of risk propensity.[15] In previous research on hybrid entrepreneurship, no evidence has been presented of this non-linear relationship between risk propensity and the likelihood of a transition or an entire failure.

Previous evidence suggests that the group of self-employed is very heterogeneous. From political perspective and in light of the increasing proportion of part-time and hybrid self-employed in Germany and Europe (Metzger and Ullrich, (2014), European Commission, (2014), and Bosma et al., (2008)), the knowledge about the factors ensuring the success and survival of ventures is of great importance. It can help develop and improve start-up programs aimed to support entrepreneurs with the best chances to survive and create employment (Fritsch and Mueller, (2007)).

Here, my findings reflect the need to investigate the entry to self-employment as a choice between part-time and full-time, and between hybrid and exclusive self-employment, respectively. Failure and transition probabilities need to be modeled as the choice between a transition to an alternatively available entrepreneurial mode (e.g. part-time to full-time) and the general exit probability. The results show that in particular risk propensity, dual job-holding, gender and parental self-employment partially change size and direction on entrepreneurial transition and survival substantially.

[15] A positive marginal effect in the estimation of the failure probability implies a lower probability of survival in the respective entrepreneurial mode.

Chapter 3

Does the Hartz IV Reform have an Effect on Matching Efficiency in Germany?

3.1 Introduction

Apart from the recent development of the European labor markets since the beginning of the financial crisis in 2007, Germany has had to deal with high unemployment rates along with a huge and persistent stock of long-term unemployed. Of all OECD countries in 2007, only France, Turkey, Poland, Croatia and Slovakia had to face higher unemployment rates than Germany, which had an average of 8.4%. Although the unemployment rate in Germany declined during 2007 and 2008, a long-term unemployment rate of 4.7% in 2007 and 3.8% in 2008 is still high compared to other OECD countries. In Germany almost 50% of all unemployed are on average unemployed for longer than one year.[1]

In addition to the broad gap between the unemployment rates in West Germany and the federal states of the former German Democratic Republic, there are also considerable disparities across regions within both former East and West Germany.[2] To relieve the large disparities between regions and to promote employment, the German government subsequently implemented a series of 'Hartz' laws.[3] These laws were part of a comprehensive reform program, which came into effect in the period 2003-2005, primarily applied to the labor market and generally known as the Agenda 2010.[4] The set of reform elements is aimed at improving the labor market services in terms of effectiveness and efficiency. To enhance the performance of the job placement process, the highly centralized institutional structure of the Federal Employment Agency was completely modernized. More specifically, it was turned into a decentralized organization

[1]Only Poland and Slovakia exhibited higher long-term unemployment rates in 2007 and 2008. See *ec.europa.eu/eurostat* for comprehensive statistics on labor market indicators

[2]See OECD Employment Outlook 2008 for further details and figures.

[3]The laws are named after Peter Hartz, the chairman of the commission that set up the policy design of those laws.

[4]In January 2003 the first two 'Hartz' laws (Hartz I, Hartz II), in 2004 Hartz III and in 2005 the fourth law (Hartz IV) came into effect.

with many job centers established by local employment agencies (Jacobi and Kluve, (2006)).

Since problematic groups among the unemployed are the low skilled, old, long-term and foreign unemployed, Hartz IV, the most radical measure, primarily aims at encouraging the unemployed as well as improving their placement process. Through the creation of sanction schemes, especially concerning unemployment benefits, unemployed are more or less forced to increase their efforts in finding a job. Before Hartz IV, unemployed received unemployment benefits infinitely regardless of whether they were actively engaged in job search or not. Nowadays, those unemployed who persistently refuse moderate[5] job offers, have to expect a reduction of their unemployment benefits after a certain period of time or a certain number of refusals.[6] Clearly, this last reform step - Hartz IV - places great emphasis on measures that promote a direct (re-)integration into the labor market as opposed to training measures, public job creation schemes and a restructuring of the federal employment agencies enacted by Hartz I, II and III.

Insofar, the question I will address in this paper is how matching efficiency has evolved over time and between regions in the course of the reform program. In particular, has Hartz IV contributed to an increased matching efficiency after its implementation in January 2005? Following Fahr and Sunde, (2006), Ibourk et al., (2004) and Hynninen, (2009), I employ a stochastic frontier function to model the matching process with both stocks and flows of vacancies and unemployed for Germany in order to evaluate the regions with the most efficient matching processes.

Furthermore, it has been proven in empirical studies (Coles and Smith, (1998), Gregg and Petrongolo, (2005), Coles and Petrongolo, (2008)), that the stock of unemployed is more likely to match up with the inflow of newly registered jobs than with the job vacancy stock. Similarly, it is more probable that an individual, having recently become unemployed, gets matched with a job belonging to the vacancy stock.[7]

[5]The definition of moderate, acceptable or suitable work has been broadened. For instance, under very limited circumstances, the unemployed are obliged to move to different regions in order to take a job.

[6]Another purpose of the reform program was to increase the flexibility of the labor market e.g. by relaxing job protection and lowering social-security contributions for certain part-time jobs, namely 'mini-jobs' and 'midi-jobs'.

[7]Coles and Smith, (1998) describe a marketplace framework to analyze the matching probability of workers by duration classes in U.K. Job Centers depending on the stocks and flows of unemployed workers and vacancies. Their results suggest, that the longer a person remains unemployed the more probable a match with an incoming vacancy compared with a vacancy from the vacancy pool. In contrast, it is more likely that the unemployment inflow matches with the vacancy stock. The findings of Coles and Smith (1998) point out the importance to examine the stock-flow interaction as a driving factor in generating new matches.

To reflect these interactions and their impact on the matching process, I select a flexible translog function as underlying framework for the stochastic frontier analysis. It rather appears as an adequate functional form to investigate whether new hirings are principally generated by the interactions of stocks and flows or simply by either stocks or flows of unemployed and vacancies. Recently, Fahr and Sunde, (2009) conducted a non-stochastic frontier analysis using monthly data from March 2000 to December 2004 to estimate the extent to which stocks and flows of unemployed and vacancies affect the matching process in the course of Hartz I - Hartz III.[8]

Summing up, this paper represents the first approach to evaluate a change in the matching efficiency in Germany mainly after the implementation of Hartz IV by applying a stochastic translog frontier to monthly data of 178 local employment agencies from January 1998 to January 2008.

The paper proceeds as follows. Section 2 introduces several functional frameworks of a stochastic frontier and the specification of the inefficiency term. Section 3 provides a description of the regional data set used for my empirical analysis. The core results of the stochastic frontier estimation and the matching efficiencies are presented and discussed in Section 4 which is followed by the conclusion in Section 5.

3.2 The Model Framework

As the estimates of the regional matching efficiencies are of particular interest, a proper stochastic frontier function has to be set up. Commonly, the matching or unemployment outflow rate is modeled by means of a Cobb-Douglas function with the stocks or both the stocks and flows of unemployed and vacancies. However, the translog function offers another approach: It relates the stocks and flows of unemployed and vacancies, their quadratic terms and crossproducts to the number of matches. Hence, it appears as an appropriate functional form that allows to investigate whether new hirings are principally generated by the interactions of stocks and flows or by either stocks or flows of unemployed and vacancies. Some critique has been presented against the Cobb-Douglas specification by Yashiv, (2000) and Warren, (1996). The next section introduces the model framework composed of a stochastic frontier function and an inefficiency term. Several functional forms will be presented, followed by a precise specification of both frontier and inefficiency term for the estimation, forthcoming in Section 4.

[8] Fahr and Sunde, (2009) estimate several fixed effects specifications of a Cobb-Douglas matching functions over 178 local employment agencies for several time intervals, but only consider data up to December 2004.

3.2.1 The Frontier Function

In principle, the matching process can be modeled as the number of matches M_{it} as a function of the stocks and flows (^{F}) of unemployed, U_{it}, U^F_{it} and vacancies, V_{it}, V^F_{it} in month t and region i:

$$M_{it} = f(U_{it}, V_{it}, U^F_{it}, V^F_{it}) TE_{it}. \tag{3.1}$$

Moreover, in case of the stochastic frontier, the number of hirings depends on an efficiency term TE_{it} allowed to vary over time and between regions. The inefficiency term enters the model as $\ln TE_{it} = -\vartheta_{it}$, where $\vartheta_{it} \geq 0$ is defined as a measure of *technical inefficiency* since $\vartheta_{it} = -\ln TE_{it} \approx 1 - TE_{it}$.[9] As frontier function $f(\cdot)$, I primarily assume a flexible translog function:[10]

$$\ln m_{it} = (\alpha_0 + \sum_k \alpha_k \ln x_{it,k} + 0.5 \sum_k \sum_l \beta_{kl} \ln x_{it,k} \ln x_{it,l} + \varepsilon_{it}) - \vartheta_{it}, \tag{3.2}$$

with $k = \{u, v, u^F, v^F\}$, thus $x_{it,u} = \frac{U_{it}}{L_{it}} = u_{it}$, $x_{it,v} = \frac{V_{it}}{L_{it}} = v_{it}$, $x_{it,u^F} = \frac{U^F_{it}}{L_{it}} = u^F_{it}$ and $x_{it,v^F} = \frac{V^F_{it}}{L_{it}} = v^F_{it}$.

m_{it} is defined as the rate of unemployment outflow to employment covered by social security. u_{it} and v_{it} enter the model as unemployment and vacancy rates at the beginning of month t. The inflow rates of unemployed and vacancies, denoted as u^F_{it} and v^F_{it}, capture all unemployed and vacant jobs which have been registered at the local employment agency (LEA) in region i during month t. All variables are adjusted by the size of the labor force L_{it} and thus reported as rates.[11] ε_{it} is a white-noise error term with $\varepsilon_{it} \sim N(0, \sigma^2_\varepsilon)$.

To find out whether the translog function is a most preferable matching framework, I estimate three specifications to allow for a comparison among them. Hence, besides the

[9] The advantage of a stochastic compared to a deterministic frontier is, that unusual effects are not necessarily considered as stochastic. In case of a deterministic frontier, imperfections, especially with respect to model specification and measurement errors, cause an increasing or decreasing efficiency over time. In terms of the model in equation (3.2), ε_{it} accounts for all the irregularities which do not coincide with a change in the efficiency. In a deterministic frontier the random error ϑ_{it} is missing. Consequently, all effects which are not measured by the explanatory variables are captured by the term ε_{it}. See Greene (2007) for an extensive survey on efficiency analysis using a stochastic frontier.

[10] See Berndt and Christensen, (1973) for a derivation of the transcendental function and its application to the U.S. manufacturing sector.

[11] Munich, Svejnar, and Terrell, (1998) argue that the variables have to be adjusted by the size of the labor force L_{it}. They demonstrate the impact of the spurious scale effect on estimation using data at the regional level. The estimation of a model without variables adjusted by the size of the regional labor force yields biased estimates in case of increasing or decreasing returns to scale. Only if the underlying matching function displays constant returns to scale or $Corr(L_{it}U_{it}) = Corr(L_{it}V_{it}) = Corr(L_{it}U^F_{it}) = Corr(L_{it}V^F_{it}) = 0$ are the estimates of an unadjusted model equivalent to those of an adjusted model.

translog function, I select the Cobb-Douglas and the nonlinear CES (Constant Elasticity of Substitution) function. The CES function imposes a constant elasticity of substitution σ among the input factors.[12] Since the CES function cannot be linearized analytically, Kmenta, (1967) derives the two-input CES function as an approximation of a linearized Taylor series given a substitution parameter ρ close to zero and, accordingly, an elasticity of substitution σ with $\sigma = \frac{1}{1+\rho}$ near to unity. The nonlinear stochastic stock-stock CES production frontier is written as:

$$m_{it} = \psi[\delta u_{it}^{-\rho} + (1-\delta) v_{it}^{-\rho}]^{-\frac{\nu}{\rho}} \cdot TE_{it} \tag{3.3}$$

with ψ as an efficiency parameter, δ and $1-\delta$ as distributional parameters describing the share of the unemployment and vacancy rates on the hiring rate. ν is the returns-to-scale parameter.[13] By means of the Taylor approximation, the nonlinear CES function corresponds to the following stochastic CES production frontier:

$$\ln m_{it} = \ln\psi + \nu\delta \ln u_{it} + \nu(1-\delta)\ln v_{it} - 0.5\rho\nu\delta(1-\delta)[\ln u_{it} - \ln v_{it}]^2 + \varepsilon_{it} - \vartheta_{it}. \tag{3.4}$$

The restricted approximation of the nonlinear CES function in equation (3.4) can be rewritten as an unrestricted version:

$$\ln m_{it} = \alpha_0 + \alpha_1 \ln u_{it} + \alpha_2 \ln v_{it} + \alpha_3(\ln u_{it} - \ln v_{it})^2 + \varepsilon_{it} - \vartheta_{it}. \tag{3.5}$$

Finally, the parameters in equation (3.4) are derived by means of the unrestricted α-coefficients:

$$\begin{aligned}
\psi &= exp(\alpha_0) \\
\nu &= \alpha_1 + \alpha_2 \\
\delta &= \frac{\alpha_1}{\nu} \\
(1-\delta) &= \frac{\alpha_2}{\nu} \\
\rho &= \frac{-2\alpha_3\nu}{\alpha_1\alpha_2}.
\end{aligned} \tag{3.6}$$

[12] In the two factor case, meaning the stock-stock matching function approach, the elasticity of substitution between vacancies and unemployed is assumed to be constant. In the stock-flow model (the four factor case) the elasticity of substitution σ between both stocks and flows of unemployed and vacancies remains constant.

[13] All parameters are strictly greater than zero except the substitution parameter ρ which has a lower bound -1.

The same transformation has to be applied to the four factor (stock-flow) stochastic CES production frontier.[14] Hence, the stock-flow approach of an approximated stochastic CES production frontier is given by:

$$\begin{aligned}
\ln m_{it} = {} & \underbrace{\ln\psi}_{=\alpha_0} + \underbrace{\nu\delta_1}_{=\alpha_1}\ln u_{it} + \underbrace{\nu\delta_2}_{=\alpha_2}\ln v_{it} + \underbrace{\nu\delta_3}_{=\alpha_3}\ln u^F_{it} + \underbrace{\nu(1-\delta_1-\delta_2-\delta_3)}_{=\alpha_4}\ln v^F_{it} \\
& \underbrace{-0.5\rho\nu\delta_1\delta_2}_{=\alpha_5}[\ln u_{it} - \ln v_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_1\delta_3}_{=\alpha_6}[\ln u_{it} - \ln u^F_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_1(1-\delta_1-\delta_2-\delta_3)}_{=\alpha_7}[\ln u_{it} - \ln v^F_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_2\delta_3}_{=\alpha_8}[\ln v_{it} - \ln u^F_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_2(1-\delta_1-\delta_2-\delta_3)}_{=\alpha_9}[\ln v_{it} - \ln v^F_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_3(1-\delta_1-\delta_2-\delta_3)}_{=\alpha_{10}}[\ln u^F_{it} - \ln v^F_{it}]^2 + \varepsilon_{it} - \vartheta_{it}.
\end{aligned} \tag{3.7}$$

The α-coefficients of the unrestricted model, similar to equation (3.5) for the two-factor case, relate to the coefficients of the restricted stochastic approximation as follows:

$$\begin{aligned}
\psi &= exp(\alpha_0) \\
\nu &= \alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 \\
\delta_1 &= \frac{\alpha_1}{\nu} \\
\delta_2 &= \frac{\alpha_2}{\nu} \\
\delta_3 &= \frac{\alpha_3}{\nu} \\
(1-\delta_1-\delta_2-\delta_3) &= \frac{\alpha_4}{\nu}.
\end{aligned} \tag{3.8}$$

The measures of substitutability or complementarity between stocks and flows of unemployed and vacancies are evaluated with $\rho_j,\ j = 1,\ldots,6$ for the four-factor case.

[14] The starting point of the approximation is the nonlinear stock-flow CES production function with $M_{it} = \psi[\delta_1 U_{it}^{-\rho} + \delta_2 V_{it}^{-\rho} + \delta_3 (U^F_{it})^{-\rho} + (1-\delta_1-\delta_2-\delta_3)(V^F_{it})^{-\rho}]^{-\frac{\nu}{\rho}} \cdot TE_{it}$. In addition to the traditional two-factor CES model, Chen and Lin, (2009) develop a three factor CES stochastic production frontier model and apply it to panel data from 15 countries over the period 1993-2003.

Given the relationships between the α-coefficients of the unrestricted and the parameters $\nu = \sum_1^4 \alpha_m$ with $m = 1, \ldots, 4$ and δ_n with $n = 1, \ldots, 4$[15] of the restricted model, the several ρ-values are

$$\begin{aligned}
\rho_1 &= \frac{-2\alpha_5 \nu}{\alpha_1 \alpha_2} \\
\rho_2 &= \frac{-2\alpha_6 \nu}{\alpha_1 \alpha_3} \\
\rho_3 &= \frac{-2\alpha_7 \nu}{\alpha_1 \alpha_4} \\
\rho_4 &= \frac{-2\alpha_8 \nu}{\alpha_2 \alpha_3} \\
\rho_5 &= \frac{-2\alpha_9 \nu}{\alpha_2 \alpha_4} \\
\rho_6 &= \frac{-2\alpha_{10} \nu}{\alpha_3 \alpha_4}.
\end{aligned} \tag{3.9}$$

As the substitution parameter ρ becomes zero, the linearized stock-flow CES function in equation (3.7), collapses to a standard Cobb Douglas function[16]

$$\ln m_{it} = \underbrace{\ln \psi}_{=\alpha_0} + \underbrace{\nu \delta_1}_{=\alpha_1} \ln u_{it} + \underbrace{\nu \delta_2}_{=\alpha_2} \ln v_{it} + \underbrace{\nu \delta_3}_{=\alpha_3} \ln u_{it}^F + \underbrace{\nu(1 - \delta_1 - \delta_2 - \delta_3)}_{=\alpha_4} \ln v_{it}^F + \varepsilon_{it} - \vartheta_{it}. \tag{3.10}$$

The results of a model selection process in section 3.4.1 identify one of these functional forms in equations (3.2), (3.5) or (3.7) and (3.10) as the most appropriate function for the stochastic frontier.

Irrespective of the functional framework, a dummy *2005:01* and 11 monthly dummies to account for seasonal fluctuations are added alongside the CES, Cobb-Douglas and translog frontier for the estimation in section 4. The dummy *2005:01*, which takes the value 1 in January 2005, is supposed to capture the structural break occurring in the data at that point.[17]

Fahr and Sunde, (2006) estimate occupational and regional matching efficiencies for 117 local employment agencies in Western Germany by applying a stochastic production frontier to yearly data from 1980-1997. They use a Cobb Douglas framework as

[15] δ_4 is computed as $\delta_4 = 1 - \delta_1 - \delta_2 - \delta_3$

[16] Like the linearized two-factor CES function, the four-factor CES function in equation (3.7) is constituted by two parts: the first part simply represents a standard Cobb-Douglas function and the second part is an adjustment driven by the substitution parameter ρ. As ρ converges to zero, the adjustment disappears and the CES function approaches the Cobb-Douglas function.

[17] The structural data break was caused by a change in the definition of the unemployment status. All social contribution recipients, who did not count as unemployed before January 2005 had to register as unemployed. Statistically, this was followed by a sharp increase in the number of unemployed, solely due to statistical reasons.

a frontier function with the stocks of unemployed and vacancies. The inefficiency term is specified in dependence on whether the analysis is conducted for occupations or for regions. Hynninen, (2009) investigates the composition of the job-seeker stock in labor market matching through a stochastic production frontier applied to monthly data from 145 local labor offices in Finland between 1995 and 2004. Hynninen, (2009) estimates a conventional random and fixed-effects model besides the three different stochastic frontier models. The matching process is supposed to follow the conditions and restrictions of a Cobb-Douglas production function. A study by Ibourk et al., (2004) analyzes the change in matching efficiencies for 22 French regions from March 1990 till February 1994. Unlike other studies, Ibourk et al., (2004) use a translog function for the stochastic frontier.

3.2.2 The Inefficiency Term

As mentioned in section 3.2.1, the efficiency term TE_{it}, with $-\ln TE_{it} = \vartheta_{it}$, represents the second part of a stochastic efficiency frontier. Battese and Coelli, (1995) have proposed a widely adopted distributional assumption of ϑ_{it} to allow for variations of both over time and across regions.[18] More precisely, they model the **in**efficiency ϑ_{it} as a function of observed characteristics, expressed by a $(1 \times K)$ vector z_{it}, which are likely to explain the efficiency of the matching technology. Hence, the ϑ_{it}-errors are denoted by:

$$\ln \vartheta_{it} = z_{it}\zeta + \omega_{it}, \tag{3.11}$$

where ζ is a $(K \times 1)$ vector of unknown parameters to be estimated. Following Battese and Coelli, (1995), I define ω_{it} with $\omega_{it} \geq -z_{it}\zeta$ as an unobservable *iid* distributed random variable, obtained by truncation of the normal distribution with mean zero and an unknown variance σ^2_{ω} and with a truncation point at $-z_{it}\zeta$. Accordingly, ϑ_{it} is a non-negative truncation of the normal distribution with $N(z_{it}\zeta, \sigma^2_{\omega})$. The technical efficiencies, conditional on the estimated coefficients of the unemployment and vacancy rates for stocks and flows as well as the hiring rate, are then computed as follows:[19]

$$\hat{\vartheta}_{it} = exp(-(z_{it}\hat{\zeta} + \hat{\omega}_{it})). \tag{3.12}$$

[18] See Aigner, Lovell, and Schmidt, (1977) for alternative distributional assumptions of the inefficiency term.

[19] The parameter estimates of the stochastic frontier and the inefficiency term are achieved simultaneously by maximizing the log-likelihood of the model. See Battese and Coelli, (1995) for a derivation of the likelihood function.

The z_{it}-vector in (3.13) is a group of variables describing the structure of the unemployed workforce, controls for the Hartz IV reform, business cycle and social and region-specific fluctuations of an economy

$$\begin{aligned} z_{it} =& (young_{it}, old_{it}, long_{it}, fem_{it}, foreign_{it}, \\ & ifo_t, HartzIV_t, PopDens_{it}, PopDens2_{it}, east_i, trend_t). \end{aligned} \tag{3.13}$$

In detail, I include the unemployment rate of unemployed workers equal to or younger than the age of 25 ($young$), of those equal or older than 55 years (old), the long term ($long$), the female (fem) and the foreign unemployment rate ($foreign$) as explanatory variables for inefficiencies.[20] The variables are likely to reflect the search intensity of these key problem groups. Although equally important and in the same space of arguments, the model does not, however, provide variables accounting for the educational attainment of the unemployed. Commonly, the share of high and low skilled unemployed is included implying higher employment probabilities of those possessing an university degree compared to individuals who neither finished high school nor obtained a vocational degree. However, due to inconsistencies in statistical recording of data on education levels of registered unemployed since 2005, I estimate the stochastic frontier model without consideration of skill attainment.[21]

Changes due to business cycle fluctuations, such as an intensified search behavior on the worker side as well as on the firm side, are comprised by the ifo index (ifo_t) - a non-district specific measure of the monthly business expectations of German entrepreneurs.[22]

Since I postulate that Hartz IV, the last step of the Hartz reforms, induces a strong effect on matching efficiency, I include an 'exponential' dummy ($HartzIV_t$). Opposed to a step dummy, switching from 0 to 1 in one period, this dummy variable exponentially increases from 0 up to 1 in 12 months according to a specific growth rate.[23] Even though Hartz IV came into effect in January 2005, agents on both sides, the local employment agencies (LEA) and the unemployed job seekers, have had to learn and adjust their placement and search intensity, respectively, according to the rules set by Hartz IV.

[20]All person more than 12 months without employment are classified as long-term unemployed.

[21]Unemployed enter the statistics not according to their obtained vocational degree but according to their career aspiration. For instance, a skilled baker who is not able to continue the profession, registers as unemployed by indicating an alternative job he or she wished to apply for in the future. Consequently, it is not recommended to draw conclusions regarding the qualification of the particular unemployed. Since January 2009 a plausible evaluation of the unemployed according to their recently obtained vocational degree is possible.

[22]There are three different indices for the business cycle provided by the ifo-Institute in Munich, Germany. In following Fahr and Sunde, (2009) I use the index R3 which reflects the business expectations.

[23]For further details on the growth rate, please contact the author.

Clearly, this justifies a dummy variable, which not immediately takes the value 1 in January 2005 when the law was implemented.

The frequency of how often contacts are established between unemployed workers and firms and how many times those contacts lead to an employment, is clearly a factor of how densely areas are populated. As a result, population density ($PopDens_{it}$) enters the inefficiency term and is meant to control for effects caused by the density of economic activities. For unemployed workers in sparely populated rural areas, the job matching is likely to be more difficult than for unemployed in densely populated urban areas.[24] However, this positive impact on the hiring rate is supposed to become negative as the area gets too densely populated. The advantage of a more developed social network and an easier access to information/media is then offset by an increased competition for jobs among the unemployed workers. To consider this turning point, a quadratic term of population density ($PopDens2_{it}$) is added to the z_{it}-vector. The dummy variable $East_i$ takes the value 1 if the LEA is located in the territory of the former German Democratic Republic. Since with Hartz I, II and III the reorganization of the Federal Employment Agency and its related LEAs has already been started, this may have exhibited an effect on the placement productivity of the LEAs. Accordingly, I include a time trend to reflect the adjusting behavior of the LEAs and other macroeconomic changes that occurred during the observation period.

In a simpler form, the inefficiency term ϑ_{it} is solely a function of time and not modeled itself by a set of explanatory variables, given by:

$$\vartheta_{it} = \eta_{it}\vartheta_i = exp(-\eta(t-T)\vartheta_i), \tag{3.14}$$

whereas the last period ($t = T$) contains the base level of inefficiency. If $\eta > 0, \eta = 0$ or $\eta < 0$, the inefficiency in region i increases, remains constant or decreases over time.

3.3 Data and Description

To estimate the stochastic frontier, I employ a highly disaggregated monthly panel data set, provided by the Federal Employment Agency.[25] The data set comprises information for 178 districts of local employment agencies (LEA) over a period from January 1998 until January 2008. 141 of the 178 LEAs belong to Western and 37 to Eastern Germany. An efficiency analysis based on this data set brings novel insight whether the Hartz

[24] Despite the substantial emigration from Eastern to Western Germany not all regions in East Germany lost a high share of their population, some even attracted people.

[25] The data is publicly available at the website of the Federal Employment Agency (*Bundesagentur für Arbeit*). Please refer to `www.arbeitsagentur.de`

reform, especially Hartz IV, has been successful in raising the matching rates throughout Germany.

To underline the strongly heterogeneous regional labor market in Germany, Table 3.1 presents the mean values of the hiring rate m_{it} and the exogenous variables entering the stochastic frontier model in equation (3.2) for overall Germany, the Eastern and the Western part. The hiring rate is measured as the outflow rate from unemployment to employment identified by social security payments. Hence, unemployed who participate in a measure of active labor market policy (ALMP) immediately before they find a job are counted as hirings from out of the labor force, as participants in programs of ALMP are not recorded as unemployed.

TABLE 3.1: Mean values (1998:01-2008:01)

Variable		Germany	East[2]	West
Hiring rate	m_{it}	0.67%	1.13%	0.55%
Unemployment rate	u_{it}	10.28%	17.89%	8.30%
Vacancy rate	v_{it}	1.07%	0.97%	1.10%
Unemployment inflow rate	u_{it}^F	1.55%	2.45%	1.32%
Vacancy inflow rate	v_{it}^F	0.64%	0.84%	0.59%

The table reports mean values over time (January 1998 to January 2008) and across the LEAs for West and East Germany. The variables are reported as rates using the total civilian labor force as reference.

It is remarkable that, compared to West Germany, the mean values of the hiring and unemployment rate as well as of the unemployment inflow rate for Eastern Germany are about twice as high. The twofold higher matching rate is likely to be a result of the higher stocks and inflows of unemployed compared to the entire labor force.[26]

The mean values of selected Z_{it}-variables are listed in Table 3.2 and primarily describe the structure of the unemployment pool. Again, the unemployment rates for East Germany, except for foreigners, are twice and in case of the female and the long term unemployment rate, nearly three times higher than for West Germany. Despite the structure of the unemployed, two important measures for an ex-ante impression of the German labor market are listed at the end of Table 3.2: The matching probability and the labor market tightness.

The matching probability ϕ indicates how likely an unemployed worker finds a job. The vacancy-to-unemployed ratio, denoted as $\theta = V/U$, represents an indicator for the

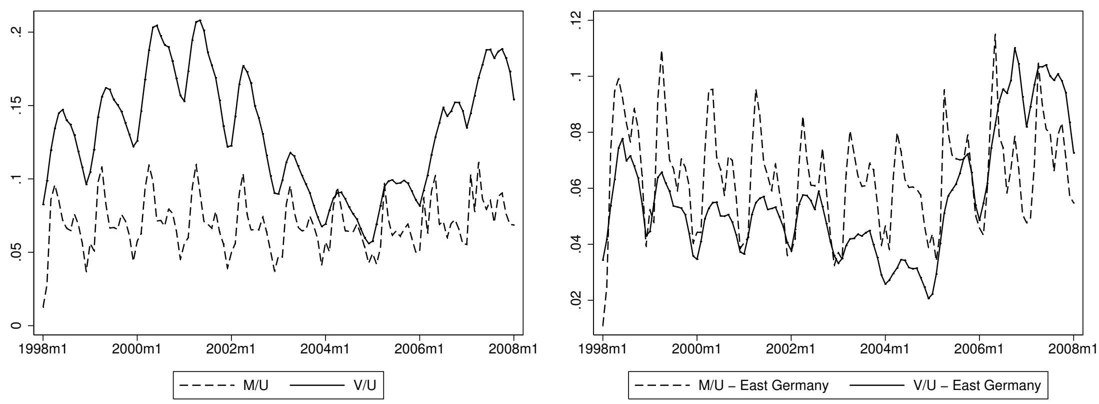
[26] According to studies of the Institute of Employment Research *IAB* in 2007 on average only 49 % of all vacancies are reported to the Federal Employment Agency by German firms. The registration rate in East Germany is somewhat higher with 52 % compared to 48 % for West Germany. More specifically, about 66% of all registered vacancies are to be filled immediately. Although not all vacant jobs are registered, it sufficiently reflects the job placement executed by LEAs and how it has been improved during the previous years.

TABLE 3.2: Mean values of selected Z_{it}-variables (1998:01-2008:01)

Variable		Germany	East	West
Unemployment rate of the < 25 years	*young*	1.21%	2.03%	0.99%
Unemployment rate of the > 55 years	*old*	1.61%	2.61%	1.35%
Long term unemployment rate	*long*	3.65%	6.56%	2.89%
Female unemployment rate	*fem*	4.84%	9.03%	3.76%
Foreign unemployment rate	*foreign*	1.11%	0.52%	1.27%
Population Density[1]	*PopDens*	428.15	326.98	454.7
Matching Probability[2]	ϕ	6.93%	6.45%	7.05%
Labor Market Tightness[3]	θ	13.16%	5.63%	15.14%

[1] The population density is reported as the number of people per square kilometer. [2] The Matching probability is simply the number of matches per unemployed, given by $\phi = \frac{M}{U}$. [3] The Labor market tightness, denoted as $\theta = \frac{V}{U}$ reflects the number of jobs per unemployed.

labor market tightness or, more precisely, how tight the number of vacancies are distributed per unemployed worker.[27] Given the descriptive statistics in Table 3.2, the East German labor market seems on average more efficient than the West German labor market. In other words, in West Germany the vacancy stock covers on average[28] 15.14% of



(A) Germany

(B) East Germany

all registered unemployed. The probability, that an unemployed gets matched with one of these vacancies during a certain time period, in this case during January 1998 and January 2008, is on average 7.05%. Contrarily, in East Germany merely 5.63% of the unemployed are assigned to exactly one vacant job position, whereas 6.45% of them

[27]The more vacancies per unemployed the tighter the labor market. Given a constant tightness θ, a labor market is said to be more efficient, if its matching probability ϕ is higher than in the other labor market with the same labor market tightness. In other words, given an identical and constant matching probability ϕ, the labor market with the lowest labor market tightness θ is the most efficient.

[28]The average is calculated for the time period from January 1998 until January 2008.

are likely to get placed in one of the vacant jobs. Figure 3.1a and 3.1b illustrates both average rates for the LEAs in Germany and East Germany over time.

3.4 Estimation Procedure and Results

This section presents the estimation results of several specifications of a stochastic efficiency frontier.[29] I will choose the appropriate functional form for the frontier in section 3.4.1, the matching efficiencies are computed in section 3.4.2.[30]

3.4.1 Selection of the Functional Framework

Initially, the stochastic frontier is estimated in a simple form, where the inefficiency term ϑ_{it} is only a function of time, as shown in equation (3.14). To allow for comparison, three alternative functional frameworks are estimated: A Cobb-Douglas (CD), a Constant Elasticity of Substitution (CES) and a translog (TL) matching function given through the equations (3)-(5), presented in section 3.2.1.

The results in Table 3.3 for the stock-stock and in Table 3.4 for the stock-flow matching functions are obtained by applying this less sophisticated framework to the data of 178 LEAs across Germany between January 1998 and January 2008. Not surprisingly, the stocks of unemployed u and vacancies v enter significantly positive. Except for the translog function (TL), the impact of the unemployment and vacancy rate declines by controlling for the inflow rates of both unemployed u^F and vacancies v^F. An 1%-increase of the vacancy inflow rate contributes to a 23% (59%) higher matching rate in case of the CD-specification (CES). As expected for the stock-stock translog matching function (TL), the coefficient measuring the interaction between unemployed and vacancies of 0.36 is significantly positive with a t-value of 29.07. In other words, 36% of all the hirings are caused by an 1% increase in the interactions of the stocks of unemployed and vacancies, relative to the entire labor force.

Subject to the hypothesis, that the stocks are more likely to interact with the inflows, this result turns out to be significantly negative in the stock-flow specification in Table 3.4. More precisely, the vacancy stock-unemployment inflow vu^F and the unemployment stock-vacancy inflow uv^F interactions enter significantly positive, whereas

[29] The estimates were carried out with FRONTIER 4.1, a computer program developed by Battese and Coelli, (1995).

[30] Basically, there are several ways of computing the matching efficiencies, either based on ordinary least squares or on maximum likelihood estimation. The advantage of the maximum likelihood approach is, that the estimates of the coefficients belonging to the frontier function and the technical efficiencies can be achieved simultaneously.

TABLE 3.3: Stochastic frontier estimation: Stock-Stock matching

$f(\cdot)$	(CD)	(CES)	(TL)
$\ln u$	0.96	0.90	1.36
	(82.57)	(55.61)	(25.85)
$\ln v$	0.29	0.35	0.93
	(73.36)	(26.49)	(32.85)
$(\ln u)^2$			-0.003
			(-0.14)
$(\ln v)^2$			0.08
			(10.48)
$\ln u \ln v$			0.36
			(29.07)
$\ln(u-v)^2$		0.01	
		(4.46)	
$2005:01$	0.12	0.11	0.07
	(6.29)	(5.98)	(4.00)
cons	-0.86	-0.86	0.01
	(-15.03)	(-18.85)	(0.37)
σ^2	0.15	0.13	0.1
	(24.32)	(23.99)	(20.24)
γ	0.62	0.59	0.53
	(51.33)	(45.85)	(21.94)
η	0.0015	0.0009	0.0013
	(8.94)	(10.57)	(10.85)
ρ		-0.01	
LogL	29.62	12.58	3623.07
N	21314	21314	21314

The model specifications include monthly dummies. t statistics in parentheses. γ is obtained by $\gamma = \sigma^2_\omega/(\sigma^2_\varepsilon + \sigma^2_\omega)$. A $\gamma = 0$ implies $\sigma^2_\omega = 0$ and indicates no variation due to inefficiency.

the interactions among the stocks uv or the flows $u^F v^F$ have a significantly negative impact on the hiring rate.

The γ-coefficient corresponds to the variance σ^2_ω of the inefficiency term ϑ_{it}. Explicitly, it states how much of the overall variance is explained by inefficiency controls. For the stock-stock model it ranges from 53% for the translog framework (TL) up to 62% in the case of a Cobb-Douglas specification (CD).[31] In contrast, the γ-value of 0.44 (0.34) for the stock-flow model is the highest (lowest) for the TL-specification

[31] 53% of the overall variance is explained by inefficiency in a functional framework specified by a translog function.

TABLE 3.4: Stochastic frontier estimation: stock-flow matching model

$f(\cdot)$	(CD)	(CES)	(TL)
$\ln u$	0.51	0.22	1.75
	(52.07)	(6.95)	(15.02)
$\ln v$	0.10	0.11	0.77
	(20.81)	(4.75)	(12.23)
$\ln u^F$	0.45	0.32	-1.08
	(53.97)	(10.81)	(-14.62)
$\ln v^F$	0.23	0.59	0.75
	(44.62)	(23.26)	(11.37)
$(\ln u)^2$			-0.42
			(-16.19)
$(\ln v)^2$			-0.01
			(-0.92)
$(\ln u^F)^2$			-0.60
			(-22.20)
$(\ln v^F)^2$			0.08
			(5.26)
$\ln u \ln v$			-0.08
			(-4.02)
$\ln u \ln u^F$			0.86
			(18.88)
$\ln u \ln v^F$			0.26
			(8.99)
$\ln v \ln u^F$			0.27
			(9.57)
$\ln v \ln v^F$			0.10
			(5.16)
$\ln u^F \ln v^F$			-0.17
			(-5.52)
2005 : 01	-0.003	0.11	0.09
	(-0.18)	(6.25)	(5.05)
cons	-0.14	0.10	0.48
	(-3.75)	(2.35)	(11.74)
LogL	2535.76	2899.84	3502.06
N	21314	21314	21314

The model specifications include monthly dummies. *t* statistics in parentheses.

(*CD*). η indicates an increasing matching inefficiency over time, as the coefficients for all specifications are significantly positive.[32]

Furthermore, the values of the log-likelihood function for the stock-stock as well as

[32] See equation (3.14) for a formal derivation of this result.

TABLE 3.4: Stochastic frontier estimation: stock-flow matching model (1998:01-2008:01)

	(CD)	(CES)	(TL)
σ^2	0.07	0.07	0.07
	(27.75)	(22.48)	(28.85)
γ	0.34	0.39	0.44
	(20.33)	(16.37)	(26.74)
η	0.0033	0.0026	0.0018
	(23.91)	(13.26)	(24.98)
ρ_1		-0.02	
ρ_2		0.18	
ρ_3		-0.47	
ρ_4		0.51	
ρ_5		-0.40	
ρ_6		0.09	
LogL	2535.76	2899.84	3502.06
N	21314	21314	21314

The model specifications include monthly dummies. t statistics in parentheses. γ is obtained by $\gamma = \sigma_\omega^2/(\sigma_\varepsilon^2+\sigma_\omega^2)$. A $\gamma = 0$ implies $\sigma_\omega^2 = 0$ and indicates no variation due to inefficiency.

for the stock-flow matching function conspicuously favor the translog function as the proper functional framework to model the matching processes by a stochastic efficiency frontier.[33]

3.4.2 The Stochastic Translog Frontier and Inefficiency Estimates

Table 3.5 displays the estimation results of a stochastic translog frontier like the Battese and Coelli specification in equation (3.11), presented in section 3.2.2.

So far, as outlined in the literature review, no other study examines the impact of stocks and flows and their interactions on labor market matching by applying a stochastic translog frontier. However, to enable a comparison with studies considering solely the stocks, I also estimate the Battese and Coelli specification for the stock-stock matching model (1) in Table 5. Similar to the studies of Fahr and Sunde, (2006) for Germany, Hynninen, (2009) for Finland and Ibourk et al., (2004) for France, the stocks of unemployed and vacancies turn out to be significantly positive. However, in contrary to

[33]The likelihood ratio test (LR), which specifies that the translog function is the best model compared to the nesting Cobb-Douglas and CES-function, cannot be rejected.

TABLE 3.5: Stochastic Translog Efficiency Frontier (1998:01-2008:01)

$f(\cdot)$	(1)	(2)	Z_{it}	(1')	(2')
$\ln u$	1.88	1.59	*young*	-0.07	-0.11
	(36.60)	(16.20)		(-4.94)	(-8.82)
$\ln v$	1.10	0.80	*old*	0.12	0.01
	(37.14)	(12.95)		(9.87)	(0.80)
$\ln u^F$		-0.73	*long*	-0.11	-0.03
		(-9.29)		(-15.14)	(-3.67)
$\ln v^F$		0.74	*fem*	0.50	0.42
		(10.78)		(18.40)	(16.65)
$(\ln u)^2$	0.28	-0.13	*non*	0.19	0.14
	(15.56)	(-5.45)		(38.37)	(30.74)
$(\ln v)^2$	0.11	-0.004	*ifo*	-0.01	-0.01
	(14.47)	(-0.39)		(-10.63)	(-13.2)
$(\ln u^F)^2$		-0.50	*HartzIV*	-0.16	-0.11
		(-17.01)		(-15.90)	(-12.60)
$(\ln v^F)^2$		0.10	*PopDens*	0.33	0.22
		(6.33)		(12.21)	(8.84)
$\ln u \ln v$	0.40	-0.02	*PopDens2*	-0.02	-0.01
	(32.62)	(-0.93)		(-9.87)	(-6.82)
$\ln u \ln u^F$		0.64	*East*	-0.29	-0.16
		(13.64)		(-20.41)	(-13.52)
$\ln u \ln v^F$		0.17	*Trend*	0.001	-0.001
		(6.07)		(6.85)	(-3.99)
$\ln v \ln u^F$		0.29	*cons*	0.72	0.71
		(9.86)		(6.63)	(7.27)
$\ln v \ln v^F$		0.07			
		(3.32)			
$\ln u^F \ln v^F$		-0.15			
		(-4.67)			
2005 : 01	0.06	0.09			
	(3.19)	(4.52)			
cons	0.60	0.55			
	(10.02)	(10.91)			
σ^2	0.06	0.05			
	(100.26)	(92.73)			
γ	0.28	0.19			
	(15.24)	(10.70)			
LogL	971.72	3013.62			
N	21314	21314			

The model specifications include monthly dummies. t statistics in parentheses. γ is obtained by $\gamma = \sigma^2_\omega/(\sigma^2_\varepsilon + \sigma^2_\omega)$. A $\gamma = 0$ implies $\sigma^2_\omega = 0$ and indicates no variation due to inefficiency. (1) stock-stock translog frontier and the corresponding inefficiency coefficients in (1').(2) stock-flow frontier and (2') stock flow inefficiency coefficients.

Ibourk et al., (2004), the interaction of stocks of unemployed and vacancies exhibits with a coefficient of 0.4 and a t-value of 32.62 a highly significantly positive impact on the hiring rate. Furthermore, the findings of Ibourk et al., (2004) suggest a concave behavior of the vacancy stock. As the coefficient of the quadratic term of the vacancy rate v^2 is 0.11 significantly positive in Table 5, I do not find support for their results. The results for the stock-flow model (2) barely differ from those obtained by the estimation of the stock-flow specification (TL) without the modeled inefficiency term in Table 3.4. The significantly positive impact of the stock-flow interactions on the hiring rate remains unchanged as opposed to the either not significant or negative impact of the stocks and flows taken separately.

The columns (1') and (2') in Table 5 present the estimates of the determinants of the matching inefficiency. Except for the rate of unemployed above the age of 55 (old) in case of the stock-flow specification (2), all variables used to significantly explain inefficiency very well. Surprisingly, the long-term unemployment rate positively influences the matching efficiency. Probably this result coincides with the positive impact of the Hartz IV reform, measured by the exponential Hartz IV dummy. The Hartz IV coefficients of both the stock-stock (1) and stock-flow (2) model enter significantly negative, indicating an inefficiency decreasing effect. Apparently, the implementation of the Hartz IV law reveals a partial contribution to a higher matching efficiency.

As in Coles and Smith, (1996), population density definitely matters in the application process for the unemployed. Intuitively, the higher population density is, the matching or placement process is less efficient. A low unemployment rate does not always go in line with an efficient placement procedure of the LEAs. Evidence for it, can be found with the significantly positive coefficient of 0.33 for the stock-stock (1') and 0.22 for the stock flow model (2'). However, due to negative coefficients of -0.02 (1') and -0.01 (2') both with t-values wide above 3, there seems to be congestion effects. Hence, as population density exceeds a certain limit, a larger population density contributes to a slightly increased matching efficiency. Probably this result can be explained by a kind of placement routine, which has been evolved in LEAs in densely populated regions.

The γ-values for the stochastic translog frontier drops to 28% and to 19% for the stock-stock and stock-flow specification, respectively.[34] Thus, given the variables which are supposed to explain the inefficiency, only 28% (19%) of the variance due to inefficiency σ_{ω}^2 is left unexplained, whereas the rest of the overall variance counts as stochastic. Compared to other studies, the γ-estimates broadly differ. For instance, Fahr and Sunde, (2009) obtained a γ of 0.81.[35] Ibourk et al., (2004) estimate that 61% of the overall variance is due to matching inefficiencies, whereas Hynninen, (2009) finds an

[34]Contrary to model (2), the time trend enters significantly negative in the stock-stock model (1), indicating a decreasing matching efficiency over time. This may imply, that the placement process of the stocks of unemployed (mainly long-term unemployed) with the vacancy stock shall be improved further on.

[35]Fahr and Sunde, (2006) include the stock and the fraction of older and younger unemployed, those with a low and a high education level, respectively, the labor market tightness and a time trend. Hence, they left out control variables for female, foreign and long-term unemployed. As their analysis is restricted to the Western part of Germany, they leave out the dummy variable to control for the strong deviations with regard to the unemployment rate, especially with respect to the problem key groups, such as long-term, female, foreign, older and younger unemployed.

insignificant γ-value of zero.[36]

3.4.3 Regional Efficiency Estimates

The ranking of the 10 regions assigned to one of the 178 local employment agencies, exhibiting the five highest or the five lowest matching efficiencies conditional on the estimates of the stock-stock model (stock-flow model) are displayed in Table 3.6 (Table 3.7). To allow for comparison with the results obtained by Fahr and Sunde, (2006), I include the efficiency estimates conditional on the Cobb-Douglas and CES frontier specification. Hereby it is important to mention, that the Cobb-Douglas (CD), the CES (CES) and the translog (TL^1) frontier functions are estimated without an explicit modeling of the inefficiency term as shown in equation (3.14). The last column in Tables 3.6 and 3.7 displays the regional matching efficiencies based on the estimated stochastic translog specification including the Z-variables to model the inefficiency term.

Apparently, the results for the stock-stock and the stock-flow matching model for the Cobb-Douglas (CD) as well as for the CES (CES) frontier do not strongly differ. Whereas regions in Bavaria close to the Czech or Austrian borders or nearby Munich (Ansbach, Freising, Kempten, Passau, Traunstein, Weilheim) belong to the five regions possessing the most efficient matching performance. Those regions exhibiting the lowest matching efficiency are in North Rhine-Westphalia in the Ruhr Area (Bochum, Dortmund, Essen, Gelsenkirchen). These results coincide with those found by Fahr and Sunde, (2006).[37]

They identify rural and thinly populated regions in Northern Germany or regions around Munich with a performance ranked among the top five regions with the highest matching efficiencies. In case of the stock-flow translog frontier model in the third column of Table 3.7 (TL^1), these results do not change, whereas they do for the stock-stock specification in Table 3.6. For the stock-stock specification, regions from Eastern Germany enter the Top 5 positions of the matching efficiency. This picture appears somewhat distorted since the regions do not belong to only one federal state. In column (TL^1) of table 3.6 Annaberg-Buchholz and Plauen (both located in Saxony), Neubrandenburg (Mecklenburg Pomerania) and Altenburg (Thuringa) in 1998 and Gotha (Thuringa) instead of Altenburg in 2007 belong to the most efficient regions in Germany. Since I do not restrict my analysis to Western Germany, as do Fahr and Sunde, (2006), but examine

[36] A γ-value of zero indicates that all deviations from the frontier function are not due to inefficiencies. In this case, the model collapses to a standard regression model, estimated by OLS.

[37] Fahr and Sunde, (2006) compute the regional matching efficiencies based on the estimates for all matches from non-employment, for matched from the home region, from neighbor as well as from non-neighbor regions.

TABLE 3.6: Average efficiency estimates for the stock-stock matching model

model	(CD)		(CES)		(TL[1])		(TL[2])	
rank	region	1998[a]	region	1998	region	1998	region	1998
1	Ansbach	0.94	Ansbach	0.97	Plauen	0.97	Stralsund	0.97
2	Traunstein	0.89	Traunstein	0.92	Neubrandenburg	0.95	Neubrandenburg	0.97
3	Kempten	0.88	Kempten	0.91	Traunstein	0.92	Frankfurt a.O.	0.96
4	Weilheim	0.84	Weilheim	0.87	Annaberg-Buchholz	0.88	Neuruppin	0.96
5	Freising	0.79	Passau	0.8	Altenburg	0.87	Stendal	0.96
174	Helmstedt	0.31	Düren	0.32	Wuppertal	0.39	Göppingen	0.42
175	Gelsenkirchen	0.29	Bochum	0.31	Dortmund	0.38	Ludwigsburg	0.4
176	Essen	0.29	Essen	0.3	Darmstadt	0.38	Berlin Süd	0.37
177	Bochum	0.29	Gelsenkirchen	0.3	Frankfurt a.M.	0.37	Berlin Nord	0.37
178	Dortmund	0.26	Dortmund	0.27	Düren	0.36	Berlin Mitte	0.37
rank	region	2007[a]	region	2007	region	2007	region	2007
1	Ansbach	0.94	Ansbach	0.97	Plauen	0.97	Stendal	0.97
2	Traunstein	0.9	Traunstein	0.93	Neubrandenburg	0.95	Neubrandenburg	0.97
3	Kempten	0.89	Kempten	0.92	Traunstein	0.93	Wittenberg	0.96
4	Weilheim	0.86	Weilheim	0.88	Annaberg-Buchholz	0.9	Stralsund	0.96
5	Freising	0.8	Freising	0.82	Gotha	0.89	Frankfurt a.O.	0.95
174	Helmstedt	0.34	Düren	0.36	Wuppertal	0.44	Frankfurt a.M.	0.45
175	Bochum	0.33	Bochum	0.34	Dortmund	0.43	Offenbach	0.43
176	Gelsenkirchen	0.32	Gelsenkirchen	0.33	Darmstadt	0.43	Hanau	0.43
177	Essen	0.32	Essen	0.33	Frankfurt a.M.	0.42	Düren	0.4
178	Dortmund	0.29	Dortmund	0.31	Düren	0.41	Wiesbaden	0.39

The regional matching efficiencies are computed from the estimated frontier specifications in Table 3.3. [1] ([2]) Efficiency estimates from a stochastic translog frontier without (with) modeling inefficiency ϑ_{it}. [a] The matching efficiency is ranked according to the average for the years 1998 and 2007, respectively.

the Eastern part as well, these results might be a probable consequence for the stock-stock translog frontier. Obviously, the interactions between the stocks of unemployed and vacancies exhibit a higher matching efficiency for these regions in Eastern Germany than the interactions between the stocks and flows of both vacancies and unemployed.

Furthermore, the last column (TL^2) in Tables 3.6 and 3.7 refer to the matching efficiencies conditional on the estimates of the Battese and Coelli specification denoted in equation (3.12). Somewhat surprisingly for both specifications the stock-stock and the stock-flow model, regions from Eastern Germany seem to be most efficient (Stralsund, Neubrandenburg, Stendal, Neuruppin, Frankfurt (Oder)). All these regions have certain characteristics in common: thinly populated, located close to the Polish border, near major cities, e.g. Berlin. On the other hand, the local employment agencies for Berlin (1201, 1202, 1203) rank amongst those with the lowest average matching efficiency in 1998. By revising the average matching efficiencies for 2007, however, Berlin experienced an increase in its matching performance. Therefore, regions from

TABLE 3.7: Average efficiency estimates for the stock-flow matching model

model	(CD)		(CES)		(TL[1])		(TL[2])	
rank	region	1998[a]	region	1998	region	1998	region	1998
1	Ansbach	0.99	Ansbach	0.98	Traunstein	0.91	Stralsund	0.96
2	Kempten	0.98	Kempten	0.96	Ansbach	0.88	Neubrandenburg	0.96
3	Traunstein	0.94	Traunstein	0.92	Passau	0.88	Eberswalde	0.94
4	Weilheim	0.93	Weilheim	0.89	Kempten	0.86	Stendal	0.94
5	Freising	0.87	Passau	0.87	Weilheim	0.82	Neuruppin	0.94
174	Ludwigshafen	0.41	Köln	0.41	Essen	0.4	Frankfurt a.M.	0.49
175	Köln	0.4	Essen	0.4	Frankfurt a.M.	0.39	Ludwigsburg	0.49
176	Essen	0.4	Bochum	0.39	Bochum	0.39	Berlin Nord	0.46
177	Bochum	0.39	Gelsenkirchen	0.39	Dortmund	0.39	Berlin Süd	0.46
178	Dortmund	0.38	Dortmund	0.38	Ludwigshafen	0.38	Berlin Mitte	0.46
rank	region	2007[a]	region	2007	region	2007	region	2007
1	Kempten	0.99	Ansbach	0.99	Traunstein	0.93	Neuruppin	0.97
2	Ansbach	0.99	Kempten	0.97	Ansbach	0.92	Stendal	0.97
3	Traunstein	0.96	Traunstein	0.94	Passau	0.91	Neubrandenburg	0.97
4	Weilheim	0.95	Weilheim	0.92	Kempten	0.9	Wittenbrg	0.97
5	Freising	0.91	Passau	0.9	Weilheim	0.87	Stralsund	0.97
174	Köln	0.53	Köln	0.51	Essen	0.52	Göppingen	0.58
175	Gelsenkirchen	0.53	Essen	0.5	Dortmund	0.51	Wiesbaden	0.58
176	Bochum	0.52	Gelsenkirchen	0.49	Frankfurt a.M.	0.51	Ludwigsburg	0.57
177	Essen	0.52	Bochum	0.49	Bochum	0.51	Mannheim	0.56
178	Dortmund	0.5	Dortmund	0.48	Ludwigshafen	0.5	Offenbach	0.55

The regional matching efficiencies are computed from the estimated frontier specifications in Table 3.4. [1] ([2]) Efficiency estimates from a stochastic translog frontier without (with) modeling inefficiency ϑ_{it}. [a] The matching efficiency is ranked according to the average for the years 1998 and 2007, respectively.

Hesse (Frankfurt (Main), Offenbach, Wiesbaden) and from Baden-Württemberg (Ludwigsburg, Mannheim) enter in 2007 the five positions at the end of the ranking.

3.5 Conclusion

Since the sequentially implemented Hartz laws - as a major part of a comprehensive labor market reform - in Germany, there has been a huge interest to evaluate their effects on labor market outcomes, such as the transition from unemployment to employment embodied by the usual matching function framework. As opposed to the last law (Hartz IV), an extensive evaluation of the first three laws (Hartz I - Hartz III) has already taken place. Hartz IV was especially aimed at improving the efficiency of the placement process as well as the willingness of the (long-term) unemployed to accept moderate job offers. Hence, this paper addresses an analysis of the change in the matching efficiency across regional labor markets in the course of the reform. In particular, this article pursues two aims: First, to estimate the impact of stocks and flows of vacancies and unemployed and their interactions as well as the impact of potential sources of inefficiency on the regional matching rate. Second, to compute the regional matching efficiencies based upon the estimates obtained in the first step. I achieve this by employing a stochastic translog frontier to data on 178 German local employment agencies covering the period from January 1998 until January 2008. More specifically, using this approach, the disaggregated hiring rate becomes a stochastic function of the determinants of the variables accounting for the behavior of unemployed workers and worker-seeking firms.

In following the technique proposed by Battese and Coelli, (1995), I identify a proper stochastic frontier function and a stochastic inefficiency term. The inefficiency term is composed of a set of variables supposed to explain the inefficiency. As opposed to a deterministic frontier, not all unusual observations have been counted as inefficiency increasing or decreasing, but instead as outliers. According to the estimation results of a simpler version of the stochastic frontier, the translog function appears to be the more appropriate functional framework compared to the commonly employed Cobb-Douglas approach and the CES-function.

Furthermore, I estimate two specifications of the matching function: A stock-stock and a stock-flow model. According to the hypothesis postulated earlier, the interactions between the stock of unemployed and the vacancy inflow as well as between the vacancy stock and the unemployed inflow exhibit a larger impact on the hiring rate than the interaction between stocks and stocks or flows and flows.

To examine whether Hartz IV has led to an increased matching efficiency in Germany, an *exponential* dummy variable is added alongside other variables, among them the unemployment rate for younger, long-term, female and foreign unemployed in the stochastic translog frontier specification. Additionally, matching efficiencies have been computed and ranked for all the local employment agencies. My findings reveal that the implementation of the Hartz IV law exhibits a significantly positive impact on the matching efficiency for both specifications: the stock-stock and the stock-flow model. The fraction of older, female and foreign unemployed appears as efficiency decreasing, whereas the younger, and the long-term unemployed exhibit a significantly improved matching efficiency.

Summing up, the stochastic translog frontier appears as a promising framework to model the matching process including the stocks and flows of the unemployed and of vacancies. The twofold structure of this approach - the frontier function and the inefficiency term - allows for an extensive examination of the matching (in)efficiency and its changes in the course of certain reforms or shocks occurred in the labor market.

Chapter 4

Impact of Welfare Sanctions on Unemployment Duration – Evidence from German Survey Data

This chapter is based on Hillmann and Hohenleitner, (2015).

4.1 Introduction

During the last two decades, many European countries went through a paradigm shift in unemployment policy from welfare towards workfare, commonly referred to as 'activation policy'. In Germany, a comprehensive labor market reform based on the so-called 'Hartz laws' led to a substantial restructuring of the unemployment and social benefit system.[1] More than 6 million people were immediately affected by the implementation of the last reform step in January 2005; 4.5 million of them became entitled to the new unemployment benefits II (UB II), commonly known as 'Hartz IV'. The 'Hartz laws' entailed an extensive monitoring and sanction system, and work requirements were strengthened radically. Under the reformed system, a person must accept any job regardless of its impact upon their occupational skills or any other external effect.[2]

The purpose of this paper, therefore, is to look beyond the imperative of getting people employed at any price. In other words, our analysis complements employment entry with labor market dropout as another probable response to welfare sanctions. Crucially, we examine the effects of German welfare sanctions — namely the 'UB II' sanctions — on unemployment outflow in both directions, i.e. our analysis considers

[1] The reforms are named after Peter Hartz, the chief of the commission that set up the design of the four reform laws. For a comprehensive overview of each reform step, see Ebbinghaus and Eichhorst, (2006).

[2] Unwelcome (long-term) effects of benefit sanctions comprise unstable employment and low wages, also below the subsistence level.

job entry and labor market dropout (also called 'non-employment') as equally plausible and important responses to welfare sanctions.[3]

We aim to demonstrate a causal connection between the use of German UB II sanctions — sanctions that are meant to encourage a swifter entry into employment — and an increased likelihood of labor market exit.

Due to continuous pressure on the part of jobcenters, sanctioned welfare recipients may increase their search efforts or accept jobs with poorer conditions. However, as not everyone will successfully find a job that pays enough for them to leave the welfare system,[4] sanctions may actually drive some of these benefit recipients to search for alternatives beyond welfare and employment. Such alternatives include living on parents', children's or a partner's income, on assets, student's assistance[5], disability pension, early retirement pay — or in some cases even on illegal work, begging or criminal activity (Ames, (2009), Götz, Ludwig-Mayerhofer, and Schreyer, (2010), Machin and Marie, (2004), Schreyer, Zahradnik, and Götz, (2012), Wolff, (2014)).

By far the majority of European studies focus on the recipients of unemployment insurance (UI) who are, on average, more likely to find a job than welfare recipients. In reality, a significant proportion of welfare recipients consists of the long-term unemployed, and only-partly-employable people.[6] Presumably, welfare recipients are, then, more likely to end in non-employment than UI recipients. However, very few of these studies on UI recipients consider exit from labor-force as a possible consequence of benefit sanctions. The purpose of this study is to fill this gap as it provides one of the first European analysis of sanctions against welfare recipients, augmenting the view on exit into employment by the exit into non-employment.

An overview of the scarce European studies on welfare sanctions — only one of which takes into account the non-employment option — is given in Section 4.2. In the remainder of this section, we introduce some of the best-known European studies of UI recipients, comprising a few studies considering the option of leaving the labor force.[7] It should be noted that for both groups of studies — of UI as well as of welfare

[3]For the remainder of the paper, we use the word 'welfare' synonymously with the German tax-based transfer, UB II, even though welfare, technically, is a hypernym. Thus, we differentiate welfare sanctions from benefit sanctions that usually refer to the receipt of unemployment insurance payments.

[4]As explained in Section 4.3.1, also *employed* people can be eligible for UB II if their earned income does not cover the minimum subsistence level of their households. Hence, eligibility to the German UB II does not only depend on the absolute amount of the claimant's earned income but also on the number of family members living in their household.

[5]Røed and Westlie, (2012) find evidence that UI sanctions in Norway increase the transition rate into education by about 200%.

[6]Only-partly-employable people comprise, for example, persons with health restrictions and persons caring for infants or for elderly and sick relatives.

[7]Other European studies on UI sanctions are provided, for example, by Cockx et al., (2011) for Belgium and Røed and Westlie, (2012) for Norway.

recipients — several of them are restricted to specific districts of a country, to certain sectors of the labor market, or to particular groups of benefit recipients and, hence, are not necessarily valid for the total of a country's benefit recipients.

For instance, Abbring, Berg, and Ours, (2005) analyze the impact of unemployment insurance sanctions on the transition rate into employment for the Dutch metal and banking sector. They estimate a positive and significant effect of sanctions on re-employment for men and women separately, whereas the effect for female unemployed with an increased transition rate of 98% for the metal industry and 85% for the banking sector turns out to be considerably higher than for males.

For Denmark, Svarer, (2010) examines a large Danish register dataset to investigate the effect of sanctions on re-employment rates in the period from January 2003 to November 2005. Svarer, (2010) obtains positive estimates for the sanction coefficient. The estimates of the time-varying effect of sanctions suggest a remarkably high effect for the first four weeks after a sanction has been imposed. However during the following eight weeks, the effect drops sharply and loses significance after thirteen weeks.

The study of Berg and Vikström, (2014) analyzes the monitoring and sanction regime of the Swedish unemployment insurance system on re-employment durations and ensuing job quality. Using combined register data sets covering the (un-)employment history of the Swedish population over 1999 to 2004, and applying an extended Timing-of-Events (ToE) approach, they find a significant positive effect of sanctions on re-employment, but an adverse effect on job quality. Whereas job exit rates increase by 23%, wages decrease by 4% and the probability of moving from part-time to full-time employment falls by 15%.

The two following studies are based on unemployment insurance register data for certain Swiss cantons. The data records the date of sanction warnings and imposition, allowing an analysis of ex-ante and ex-post effects. Firstly, Lalive, Ours, and Zweimüller, (2005) find that both warnings and enforced sanctions affect the unemployment exit rate positively. Their model reveal a 28% shift in the unemployment exit rate after a warning. The transition out of unemployment increases again by 23% after a sanction was enforced. Compared to the effect of sanction enforcement, the results already indicate that the warning exhibits a quantitatively similar effect. Using the same administrative data source, Arni, Lalive, and Ours, (2013) employ a multivariate mixed proportional hazard model for competing risk to examine the impact of warnings, and how the imposition of sanctions affect the unemployment exit hazard to either regular employment or non-employment (i.e., out of labor force) as the two competing risks. This elaborate analysis shows a positive impact of warnings and sanction enforcements on unemployment exit rates to either of the two competing risks, whereas the announcement of a sanction increases the risk of exit to non-employment considerably. Beyond examining the unemployment exit hazard, Arni, Lalive, and Ours, (2013) amplify their approach by including an analysis of the post-unemployment employment periods with respect to job stability and earnings. They find significant evidence that a sanction during a period of unemployment reduces the duration of the first employment and non-employment period. Regarding wages, sanction warnings and impositions significantly lower post-unemployment earnings.

Similar to other European countries, in Germany the initial studies on benefit sanctions have focused on UI receipt. Müller and Steiner, (2008) explore the ex-post effect of unemployment benefit sanctions on unemployment-to-employment transitions between 2001 and 2004 separately for West and East Germany. They restrict the sample to unemployment insurance (UI) and unemployment assistance (UA) inflow cohorts in the years 2001 and 2002 at the beginning of the unemployment spell.[8] Combining propensity score matching with a discrete-time hazard rate model, Müller and Steiner, (2008) find robust positive effects of benefit sanctions for men and women in East and West Germany. The effect decreases with elapsed unemployment duration until the sanction is imposed.

Hofmann, (2012) investigates the ex-post effect of sanctions on an individual's likelihood of gaining regular employment, holding an irregular job, or leaving the labor force. A dynamic matching approach is applied to a sample of individuals that entered UI receipt between April 2000 and March 2001 in West Germany. The results reveal rather ambiguous effects: while the Average Treatment effect on the Treated (ATT) for the outcome of entry to regular employment turns out to be positive and mainly driven by young UI recipients, the ATT for the probability to hold an irregular job is positive for women but negative for men. The positive effect for women is driven by the older subgroup and the negative effect for men is found to be stronger in regions with higher unemployment rates. Regarding the outcome of leaving the labor market, benefit sanctions lead to a higher drop off within the group of older women. Also, sanctioned men have a higher probability of withdrawing from the labor market when compared to non-sanctioned men.[9]

However, given the considerably higher proportion of welfare recipients compared to UI recipients, the extensive monitoring and sanction regime introduced under 'Hartz IV', and the fact that these strengthened regulations primarily target UB II recipients, we

[8] In contrast to UI, UA was tax based. Both existed until the end of 2004. Since 2005 the unemployment benefit system has changed substantially. Further information is given in Section 4.3.

[9] This result is especially found for men who have been sanctioned during the 2nd or 3rd stratum, i.e. during the 3rd until 6th month of UI receipt.

have chosen to put the focus on unemployed welfare recipients. We provide the first analysis of the causal ex-post effects of German welfare sanctions — namely UB II sanctions — on the hazard rates to both employment and non-employment. We examine the effects on unemployment duration after the imposition of benefit sanctions, referred to as ex-post effects, and abstract from ex-ante effects, caused by implementing and tightening up the monitoring and sanction regime, or by possible warnings before imposing a sanction.

In contrast to previous studies of benefit sanctions, we estimate the effect on all employable household members, and not just on the recipient of the sanction, as UB II applies to households.[10] As a consequence, we also treat the other household members as affected. We exploit data from a novel German panel survey, especially designed for research on employable welfare recipients and their household members. It provides detailed information about individuals' (un-)employment histories, including information on UB II sanctions and periods of non-employment. Employing a Timing-of-Events (ToE) approach, we estimate a discrete Multivariate Mixed Proportional Hazard (MMPH) model to the survey data that covers the first three years after the implementation of 'Hartz IV', from 2005 to 2007.

The remainder of the paper is organized as follows: Section 4.2 briefly summarizes research on the effects of sanctions upon welfare recipients in Europe, and Section 4.3 outlines the institutional structure of the German unemployment benefit and sanction scheme implemented by the 'Hartz IV' law. A detailed description of the data, in particular of the group differences between sanctioned and non-sanctioned unemployed in UB II receipt, is provided in Section 4.4. Section 4.5 introduces the econometric model, whereas the results are presented and discussed in Section 4.6, followed by a conclusion in Section 4.7.

4.2 Research on Sanctions upon Welfare Recipients in Europe

To date, the study of welfare sanctions in European countries have been very limited. So far, there have been two studies focusing on welfare recipients in Rotterdam (Netherlands), one recent study in Finland, and three studies in Germany.

An early Dutch study on welfare sanctions is provided by Berg, Klaauw, and Ours, (2004). They use a Mixed Proportional Hazard (MPH) model and find sanctions to

[10] Unlike the individually-granted unemployment insurance benefit, UB I, the means-tested social benefit UB II applies to an entire household as a so-called 'need unit', i.e. to all related members of a household. More detailed information on the institutional framework is given in Section 4.3.

have a significantly positive effect on the unemployment-to-employment hazard of welfare recipients in Rotterdam. In figures, a sanction raises transition rates to work by 140%. Moreover, they find a substantially negative effect on the probability an individual becomes long-term unemployed if the sanction is imposed at a relatively early stage. The more recent Dutch analysis for the same municipality by Klaauw and Ours, (2013) investigates the effects of re-employment bonuses and benefit sanctions on the re-employment probability of welfare recipients and find that benefit sanctions exhibit positive effects on employment probability, whereas re-employment bonuses are not verified as an effective policy instrument.

A very recent study by Busk, (2014) compares the effects of unemployment insurance and welfare sanctions in Finland with respect to the outcomes employment, participation in the Active Labor Market Program (ALMP), and exit from labor force. Using the Timing-of-Events (ToE) approach, Busk, (2014) finds evidence for a positive effect of ongoing sanctions upon UI and welfare recipients on taking up employment as well as for completed sanctions upon welfare recipients.[11] However, she found no effect of completed UI sanctions on transition rates into employment. Regarding participation in the ALMP, sanctions have a slight positive effect on welfare recipients, but no effect on UI recipients. Finally, she found exit from labor force positively affected by both UI and welfare sanctions. This study for Finland — together with our German study — are the first European analyses of welfare sanctions considering the non-employment option.[12] The majority of the earlier German studies on benefit sanctions focused on UI recipients. However, since the 'Hartz IV' law came into force in January 2005, welfare recipients — namely UB II recipients — have come increasingly into the focus of political discussion and, with it, also into the focus of scientific research. But still, research on the effects of German welfare sanctions is very limited, and none of the previous studies take into account the non-employment option.

A very early and comprehensive research on German UB II recipients provided by Schneider, (2008) and Schneider, (2010), analyzes the effect of UB II sanctions on reservation wages, job search effort, and employment outcome using the German cross-sectional survey of unemployed UB II recipients in January 2005. Adopting a matching on propensity approach, Schneider, (2008) and Schneider, (2010) finds only the effect on unsubsidized employment as partially significant and positive; the remaining effects on reservation wages, job search effort, and subsidized employment proof neither

[11] Unlike other studies, Busk, (2014) distinguishes between effects during the periods of benefit cut (ongoing sanctions), and the effects after the benefit cuts (completed sanctions).

[12] The Finish welfare recipients in this study differ quite a lot from the German UB II recipients as the Finish UI is voluntary and, hence, the proportion of welfare recipients in Finland with good labor market prospects can be expected to be considerably higher than in Germany.

statistically nor economically significant.[13] The positive impact on unsubsidized employment turns out to be larger if the sanction is imposed earlier within the period of benefit receipt.

Using an uniquely combined data set of German administrative and survey data for unemployed in UB II receipt between 2006 and 2007, Boockmann, Thomsen, and Walter, (2014) estimate the effect of benefit sanctions on the transition from welfare receipt to unsubsidized employment. Assessing the potential bias due to sanction endogeneity, Boockmann, Thomsen, and Walter, (2014) employ an instrumental variable regression (with both the reported sanction strategy and the sanction frequency rates of 154 German welfare agencies as instruments) to measure the effectiveness of an intensified sanction regime by means of the Local Average Treatment Effect (LATE). Boockmann, Thomsen, and Walter, (2014) find evidence that benefit sanctions increase the probability to leave UB II receipt for employment within six months after the benefit cut by about 58 percentage points. Based on the results, they support a tighter use of benefit sanctions as it is supposed to increase the probability of leaving welfare dependency towards unsubsidized employment.

A recent study by Berg, Uhlendorff, and Wolff, (2014) focuses on the effect of mild and strong sanctions, applied to unemployed young male UB II recipients in Western Germany from the time they first received welfare payments until they took up unsubsidized employment.[14] The data set is limited to an inflow sample into unemployed UB II receipt of 'young adult' men, aged 18 to 24 years, during January 2007 and March 2008.[15] Berg, Uhlendorff, and Wolff, (2014) apply a Timing-of-Events (ToE) approach with two dynamic treatments (mild and strong sanctions); the results indicate that strong (mild) sanctions increase the transition rate from welfare without employment to unsubsidized work by 120% (37%).

[13] In the studies by Schneider, (2008) and Schneider, (2010), unsubsidized employment means jobs with an income that is high enough to leave UB II receipt. As it is not restricted on hours worked, it includes also part-time employment. In contrast, subsidized employment includes regular jobs with supplementary UB II receipt. This implies, also a regular (full-time) job with a low income that not sufficiently covers the minimum subsistence level of the employed and related household members, is defined as subsidized employment.

[14] Similar to the studies by Schneider, (2008) and Schneider, (2010), also Berg, Uhlendorff, and Wolff, (2014) define unsubsidized employment as a job, which is paid well enough to leave (supplementary) benefit receipt.

[15] On average, the group of 'young adults' are sanctioned more often and more tightly than older UB II recipients, see Section 4.3.2.

4.3 Unemployment Benefit and Sanction Scheme in Germany

Before 2005, the structure of the German unemployment benefit system comprises three main elements: unemployment insurance (UI) benefits, unemployment aid (UA), and social assistance (SA). The former were not means-tested, the latter two were both tax-based and means-tested. The 'Hartz IV' law merged unemployment and social assistance into the Unemployment Benefit II (UB II), whereas unemployment insurance benefits became UB I, but with stronger eligibility conditions.[16]

4.3.1 The Means-tested Unemployment Benefit System

The means-tested UB II provides basic social security for 'needy job-seekers' and their related household members. Technically, every person, who lives in Germany and is between the employable ages of 15 to 64 years and is able to work at least three hours per day, but is not able to cover the substantial needs of their household, satisfies the eligibility criteria for UB II.[17] As UB II is means-tested, recipients and their household members are classified as 'needy' but do not necessarily have to be unemployed.

In contrast to insurance benefit UB I, which is granted individually, the means-tested UB II applies to households, or the so-called 'need units'.[18] A 'need unit', also referred to as a 'need community' (*'Bedarfsgemeinschaft'*), consists of at least one person capable of working. The partner, regardless of their marital status and any children younger than 25 years belong to the 'need unit', as long as they share the same household.[19]

The heterogeneous group of UB II recipients includes people who are unemployed but not entitled to insurance benefit UB I, or whose UB I or earned income is below the household's subsistence level. Normally, individuals end up in UB II receipt after they have exceeded their maximum period of UB I receipt (in most cases, 6–12 months), and most of them are henceforth classified as long-term unemployed.[20] Another group of UB II recipients is represented by people who did not pay (sufficient) contributions to unemployment insurance, such as former pupils, students, self-employed persons or employees who worked for less than 12 months within the eligibility period of three years (before 2007) or two years (since January 2007), respectively.

[16] Social assistance (SA) is still left for needy persons who are neither eligible to UB I nor to UB II.
[17] The eligibility requirements of UB II are codified in the Social Code Book II (SCB II).
[18] Henceforth, 'household' and the official term 'need unit' are used interchangeably.
[19] Persons who live together as a merely flat-sharing community do not belong to the same household in the sense of the SCB II.
[20] As defined in the German Social Code Book III (SCB III), long-term unemployed are persons registered as unemployed at least for one year.

In comparison to the former UA, UB II is granted under tightened acceptance regulations. Whereas UA provided protection against loss of job quality and income to a certain extent, UB II recipients are obliged to accept or hold any jobs they are physically, intellectually, and mentally able to. In other words, this ignores their professional experience while also affecting the possibility of future skilled employment.[21]

Key tools of the comprehensive monitoring scheme in Germany are the 'integration contract' (*'Eingliederungsvereinbarung'*) and the appointments of 'personal case managers'. Explicitly, the integration contract specifies the duties of clients with respect to job search activities. It can determine further oligations, e.g., more or less specified commitments to participate in a program of Active Labor Market Policy (ALMP).

4.3.2 Sanctions

In consequence of the paradigm shift towards 'activation policy', with the 'Hartz IV' law a comprehensive monitoring and sanction scheme has been established.[22] Additionally, case managers are encouraged to strictly apply UB II sanctions. While the number of UB II recipients in the last years have decreased from around 5.3 million people in 2007 to 4.4 million in 2014,[23] the number of imposed sanctions per year increased — after fluctuating around 750,000 from 2007 to 2009, it finally exceeded one million in 2012, where it has remained quite stable until 2014.[24] Apparently, sanctions in form of temporarily benefit cuts — principally lasting three months — have become a crucial instrument in the German welfare policy. This is all the more weighty, as repeated sanctions can swiftly lead to a total loss of UB II, including accommodation benefits.[25]

Recipients of UB II are exposed to sanctions for a broad range of reasons such as insufficient job search effort, refusing to sign an 'integration contract',[26] non-acceptance of job offers or an offer for an integration measure, resigning a job contract, or provocation of a dismissal from a job or an integration measure. These failures are considered as *major* 'breaches of duty' and cause a 30% reduction of the base benefit in the first step. Repeated major failures within one year increase the penalty: the second failure is sanctioned with a 60% cut, the third with a total cut of UB II, including housing benefits. Further justifications for sanctions are missing appointments with case managers,

[21] Even employed persons, receiving supplementary UB II (the so-called *'Aufstocker'*) are strictly encouraged to search for additional or better paid jobs in order to reduce their means dependent benefits.

[22] The legal basis of the UB II sanction scheme is regulated in §§31, 31a, 31b, and 32 SCB II.

[23] These numbers represent the annual average of the monthly stock of employable UB II recipients.

[24] Source: publicly available statistics of the Federal Employment Agency (FEA).

[25] UB II consists of the base benefit, housing or accommodation costs, and social security contributions.

[26] While refusing to sign an 'integration contract' is no longer a legal justification for imposing a sanction, this was not the case during our observation period (2007 to 2010).

or missing medical or psychological treatments. Initially, these types of non-compliant behavior, classified as *minor* 'breaches of duty', reduce base benefit by 10%, followed by an increase of 10% points for each recurrence. Young UB II recipients, between the ages of 15 to 24 years, are sanctioned even harder. Apart from minor mistakes (missed appointments), already the first failure entails an immediate 100% cut of the base benefit, the second yields a total cut of UB II, including housing benefits.

In fact, unemployed in the last sanction step face the very real risk of homelessness. Hence, it can be expected that such a sanction scheme increases compliance and concessions on the expected job quality, particularly of unemployed who already experienced a sanction.

4.4 Data

Our analysis is based on a novel German panel survey 'Labour Market and Social Security' (PASS).[27] It is an annual household survey in the field of German labor market and welfare state research, conducted at the request of the Institute for Employment Research (IAB), and provided by the Research Data Center (FDZ) of the IAB.[28] The PASS survey is especially developed and provided for (internal and external) research on UB II and for comparisons between benefit recipients and the total population.

The PASS survey enables us to contribute to previous research on welfare sanctions in the following two points: First, we analyze the effects of sanctions on the transition rates not only to employment but also to non-employment, and second, we consider the impact of being indirectly affected by sanctions caused by other members of the 'need unit'.[29] Because of these merits of the PASS, we accept the drawbacks of a complex survey design and the associated typically human recall errors, yielding under-reported sanction events.[30]

[27] The abbreviation is based upon the German survey title, *Panel Arbeitsmarkt und Soziale Sicherung* (PASS).

[28] The FDZ (*Forschungsdatenzentrum*) of the IAB provides researchers access to micro data for non-commercial empirical research in the fields of social security and employment.

[29] Concretely, we assume and treat all employable household members as affected by a sanction. However, the low number of exclusively indirectly sanctioned individuals in our sample does not support a proper application of distinct estimations for direct and indirect sanctions separately. The task of disentangling the effects of direct sanctions (applied to the person itself) from the indirect ones (applied to another household member) should be the focus of further research on welfare sanctions.

[30] Furthermore, the conceivable alternative for us as researchers outside of the IAB, to use a Scientific Use File (SUF) that is a 2% random sample of administrative data (the so-called *Sample of Integrated Labour Market Biographies*, or SIAB for short), lacks information on exact sanction periods and the household context. However, this information is crucial for our analysis, and hence, the SIAB is not a suitable alternative for our research target.

4.4.1 General Description of the Survey Data

The PASS study consists of annual panel data on individual and household level as well as several datasets describing the entire employment history of individuals and the episodes of households' UB II receipt since January 2005. We exploit the first two waves of the survey.[31] For the first wave about 18,954 individuals, belonging to 12,794 households, were interviewed between December 2006 and July 2007. The second wave, conducted between December 2007 and July 2008, covers 12,487 persons in 8,429 households. Summing up, there are over 10,000 employable individuals in the age of 15 to 64, living in more than 7,300 households, who had been interviewed in both waves.

As the PASS is targeted towards low-income households and unemployed, the survey is structured as follows: There are two sub-samples, the *FEA-sample* which covers households and individuals entitled to UB II, and the *Microm-sample* that covers households and individuals registered as German residents. The latter is a stratified sample where the probability of a low-income (medium-income) household to be interviewed is 4 times (2 times) the probability of a high-income household. Consequently, UB II recipients and low-income earners are disproportionately represented. This is one of the PASS study's great advantages, as this segment of the population is more difficult to reach and follow up over time, and hence normally under-represented in surveys.

Besides unemployment spells, the survey comprises employment spells and — in comparison to administrative data — highly beneficial 'gap spells', recording the periods out of labor force explicitly. The detailed information in the various spell datasets enables us to track households' UB II receipt and individuals' transitions out of unemployment. Both unemployment and employment episodes are reported on a monthly frequency since January 2005. The UB II spells, reported on household level, cover detailed information on imposed sanctions, such as the type of accused violation, the date of the sanction enforcement and its duration. The survey set further comprises information on socio-demographic characteristics like individuals' household structure, labor market status, earned income, and households' net income including any kind of social benefits. Moreover, there are several subjective indicators like employment orientation and experienced social status.

[31] An extensive documentation on the first two waves of PASS is provided by Christoph et al., (2008) and Gebhardt et al., (2009).

4.4.2 Sample Selection

Our analysis covers the calendar years of 2005 to 2007. We select all individuals between 15 and 64 years that were interviewed in both of the first two waves that entered unemployed UB II receipt within the observation period.

As the spells of UB II receipt are recorded on household level, the information on imposed sanctions is also reported on household level. Even though it is possible to attribute sanctions to household members who cause it, we consider all household members as affected by sanctions. Hence, from the moment the first sanction is imposed, we classify all employable household members as sanctioned. This appears reasonable, as UB II receipt applies to households, and thus, the entire household is exposed to the budget cut.

4.4.3 Description of the Sample

Our final sample consists of 3,996 unemployment spells, whereas 742 end with a transition into employment, 601 with a transition out of labor force, and 2,653 are right censored, i.e. the persons remained unemployed until December 2007. The final sample records 3,599 unemployed persons from 15 to 64 years, who had received UB II at least for one month in the respective period from January 2005 to December 2007. 391 of them (that is 10.86%) had been sanctioned.

TABLE 4.1: Sanction Rates of Selected PASS Data (2005–2007)

Sex/Age Group	Individuals	Sanction Rate[1]
All	3,599	10.86
Men	1,533	11.29
Women	2,066	10.55
15–24 years	605	12.56
25–49 years	2,067	11.66
50–64 years	927	7.98

Source: Own calculations based on selected data of the PASS survey. [1]Percentage sanction rates, calculated as share of sanctioned unemployed UB II recipients in the period between January 2005 and December 2007.

Table 4.1 depicts the ratios of sanctioned unemployed UB II recipients who had been affected by at least one sanction between January 2005 and December 2007 in relation to all unemployed people who received UB II at least for one month within this period.[32]

The sanction rate of 'young adults' (15–24 years) is with 12.56% considerably higher, whereas the sanction rate of persons above 50 years is with 7.98% considerably lower than the total sample average of 10.86%.

Table 4.2 provides summary statistics of the basic explanatory variables of our final sample, differentiated according to persons with or without a sanction, drawn from individual data (PANEL) and spell properties (SPELL). As the survey starts in 2005, it lacks sufficient information on previous employment states. Therefore, we decide to refrain from capturing state dependence by explicit control variables but approach capturing by means of unobserved heterogeneity terms.

At first glance, the mean values in Table 4.2 reveal a fairly homogeneous picture between sanctioned and non-sanctioned unemployed. In both groups, men and women are equally represented. Negligibly but still significant more non-sanctioned UB II recipients live in eastern Germany. From the continuous variable *age* we derive three age-group dummies, whereby *age24–* contains all unemployed individuals with an age between 15 and 24 years. Correspondingly, *age50+* takes the value one for unemployed that are between 50 and 64 years old. To non-sanctioned unemployed, UB II recipients with a sanction are, on average, with 38 years about 2 years younger, have with 20.1% (19.9%) a higher (lower) proportion of individuals younger (older) than 25 (49) years and rather live without a partner in the same household. The share of the two age cohorts (*age24–* and *age50+*) in either group reflects legal regulations and common practice of sanction enforcement: Case managers are explicitly obliged to sanction young adults below 25 years more strongly, whereas persons above 50 years are treated less strictly, yielding a share of elder UB II recipients (29.3% for *age50+*) that exceeds the share of the younger (15.2% for *age24–*).

Households with children below the age of six (*child6*) account for a similar part of around 20% in both groups. With respect to the (vocational) qualification level, we differentiate between three skill groups. The levels *high skilled* refers to unemployed holding a university degree, *med skilled* comprises individuals with a secondary or high school certification or any type of successfully accomplished apprenticeship. The remaining fraction of unemployed without any degree serves as a reference (*low-skilled*).

[32]The sanction rates depicted in our study are different from others, especially from administrative data. First, they depend on the observation period: the longer considered unemployment episodes last, the longer unemployed are at risk to be sanctioned, and hence are more likely to be sanctioned within the observation period. Second, the official sanction quotas, reported by the FEA, are based on the share of *currently* sanctioned persons within a month. In contrast, we consider a person as sanctioned *beyond* the sanction period.

TABLE 4.2: Summary Statistics of Selected Variables[1]

Variable	Non-Sanctioned	Sanctioned
PANEL DATA		
woman	0.576	0.564
east***	0.399	0.364
age***	40.28 (0.032)	37.91 (0.088)
age24–**	0.152	0.201
age50+***	0.293	0.199
couple***	0.311	0.262
child6	0.188	0.201
med skilled	0.595	0.561
high skilled	0.081	0.084
migrated*	0.267	0.226
non-monetary	0.800	0.816
monetary	0.534	0.511
social**	0.887	0.869
SPELL DATA		
exit to employment**	0.109	0.130
exit to non-employment	0.098	0.094
d4–6***	0.117	0.111
d7–12***	0.210	0.208
d13–36***	0.546	0.565

Source: Own calculations based on selected data of the PASS survey. [1]Means are calculated over 93913 person months of unemployed UB II receipt within January 2005 and December 2007, comprising 3996 UB II spells, 3586 non-sanctioned and 410 sanctioned persons. Standard deviations are given in parentheses. Two-sided mean comparison tests (t-tests) give significance levels of $*10\%$, $**5\%$, $***1\%$. Current unemployment durations (measured in months) are represented by the dummies *d4–6*, *d7–12*, and *d13–36*.

The dummy variable *migrated* indicates whether or not UB II recipients have an immigrant background, meaning that they either migrated themselves (first generation), or they have at least one parent who migrated (second generation).

The PASS survey, furthermore, provides information about general attitudes to work. The dummies *non-monetary*, *monetary* and *social* indicate, whether a specific motivation is crucial for the person. The answers are not mutually exclusive, and individuals may report more than one (or none) of the three inquired working motives as important. On average, the share of UB II recipients that evaluate working as important in order to participate in society (*social*) is with 86.9% about 1.8% points significantly lower for sanctioned than non-sanctioned UB II recipients.

SPELL data provide a first impression about the probable effect of benefit sanctions on employment and leaving the labor market. Apparently, a higher share (13.0%) of sanctioned unemployed exit to employment compared to the non-sanctioned group

(10.9%). Concerning unemployment duration, half of the UB II recipients in both groups come up with a duration of more than a year. In general, the share increases with duration and remains insignificantly different in means between the two groups.

4.5 Multivariate Duration Analysis

In this paper, we examine the effects of sanctions on the transition rates of unemployed UB II recipients into employment or non-employment. In particular, we focus on the effect after the imposition of a benefit sanction, commonly referred to as ex-post effect.[33] For our analysis, we set up a model that accounts for individual's unemployment duration dependence. From the beginning of each unemployment spell, the individuals are at risk to switch to one of the two probable states in time T: become employed (e) or exit the labor market and enter non-employment (ne). If neither occurs, the individual remains unemployed and the respective spell is classified as censored ($c = 0$). Let t_e be the corresponding duration until exiting unemployment for a job, and t_{ne} be the time until the unemployed leaves the labor market.

For each period of unemployment, we observe the point in time, T_s, of a sanction enforcement and the respective time, t_s, until the individual experiences their first sanction.[34] Even though our final sample is already restricted to unemployed UB II recipients, there are still numerous observed and unobserved components, causing a non-negligible correlation between the probability of a sanction and unemployment duration. As a consequence, we cannot treat the effect of a sanction and, in particular, the time until a sanction t_s as exogenous.

In order to disentangle the effects of an unemployment benefit sanction from other observable or unobservable factors influencing the exit from unemployment, Abbring and Berg, (2003a) and Abbring and Berg, (2003b) developed the Timing-of-Events (ToE) approach, enabling a causal identification of dynamic treatment effects of imposed sanctions on the exit hazard of unemployed. The elaborate technique reveals the causal from the selective effect of an imposed benefit sanction on unemployment duration.

To analyze the duration t_o with $o \in \{e, ne\}$ until the point of transition in T_o, we employ a discrete Mixed Proportional Hazard (MPH) framework. The exit rate to either

[33]After a sanction is imposed, a mixture of ex-ante and ex-post effects occur. As people are both backward-looking and forward-looking, ex-ante effects caused by the threat of recurrent sanctions affect the outflow behavior of UB II recipients. Sticking to terms, the effect after a sanction is labeled as ex-post effect in the literature, see Lalive, Ours, and Zweimüller, (2005) and Arni, Lalive, and Ours, (2013).

[34]It is a common approach in the literature to evaluate the effect of the first sanction solely, see Berg, Klaauw, and Ours, (2004), Abbring, Berg, and Ours, (2005), Lalive, Ours, and Zweimüller, (2005) and Svarer, (2010).

destinations $o \in \{e, ne\}$, conditioned on the months elapsed until the sanction enforcement t_s, is given by:

$$\theta_o(t_o|x, \upsilon_o, t_s) = \lambda_o(t_o) exp[x'\beta_o + \delta I(t_s < t_o) + \upsilon_o], \tag{4.1}$$

where $\lambda_o(t)$ represents the baseline hazard (duration t until exit to state o). x is a vector of observables, describing individual characteristics and controlling for local labor market conditions. The dummy variable $I(t_s < t)$ indicates whether a sanction has been enforced during the unemployment spell. Hence, $I(\cdot)$ takes the value one if the time interval until a sanction has been imposed t_s is shorter than the interval until exit t_o or shorter than the entire unemployment spell in case of a censored record. υ is a random term, controlling for the unobserved components presumably affecting the hazard rates. The corresponding conditional density function of $\theta_o(t_o|x, \upsilon_o, t_s)$ is

$$f_o(t_o|x, \upsilon_o, t_s) = \theta_o(t_o|x, \upsilon_o, t_s) \exp(-\int_0^{t_o} \lambda_o(\tau|x, \upsilon_o, t_s) d\tau). \tag{4.2}$$

As unemployment duration is measured in months, we specify a discrete MPH for both probable states $o \in \{e, ne\}$ and adopt the common flexible piecewise-constant step function approximating the duration dependence of the baseline hazard

$$\lambda_o(t_o) = exp[\sum_k \lambda_{o,k} D_k(t_o)] \tag{4.3}$$

for $k = 1, ..., 4$ fixed time intervals. $D_k(t_o)$ denotes time-varying dummy variables equal to one in the corresponding interval and $\lambda_{o,k}$ the estimated parameters for the specific interval k. According to the distribution of the unemployment duration, we define the following intervals (in months): [0–3]; (3–6]; (6–12]; (12–36]. We set $\lambda_{o,1} = 0$ for the first time dummy ($k = 1$) to avoid collinearity in an estimation with a constant term.

Again, the probability of a sanction during the receipt of UB II is likely to be endogenous. Unemployed that do not comply with entitlement requirements or do not behave according to compliance commitments are at risk to experience a sanction. Here we can expect that this type of behavior, in turn, affects the unemployment duration of the individuals, entailing a correlation between the unobserved components of the two processes. Hence, both the hazard of being sanctioned and the hazard of exiting unemployment to one of the two states e, ne must be estimated jointly.[35]

[35] Here, one may argue that a MPH analysis with the exit to employment and non-employment as two competing risk should have been applied instead of treating the two processes independently. However, due to the limited number of surveyed individuals in our data, we run into convergence problems of the likelihood function.

Similar to the unemployment exit hazard, also the hazard rate of being sanctioned $\theta_s(t|x,\upsilon)$ is assumed to follow a MPH specification

$$\theta_s(t_s|x,\upsilon_s) = \lambda_s(t_s)exp[x'\beta_s + \upsilon_s], \tag{4.4}$$

with $\lambda_s(t_s)$ as duration dependence. For a parsimonious but flexible estimation, we specify $\lambda_s(t_s)$ as a quadratic function of log-time. The respective conditional density of $t_s|x,\upsilon_s$ is

$$f_s(t_s|x,\upsilon_s) = \lambda_s(t_s|x,\upsilon_s)\exp(-\int_0^{t_s}\lambda_s(\tau|x,\upsilon_s)d\tau). \tag{4.5}$$

Based on the modeling framework so far, the joint distribution of the processes $t_o|t_s,x,\upsilon_o$ and $t_s|x,\upsilon_s$ can be fully described by the proposed Mixed Proportional Hazard (MPH) specification. Thus, the hazard of the latent failure (either unemployment exit or the hazard being sanctioned) depends on the duration t_o,t_s until this event occurs in T_o,T_s, on the observable characteristics comprised by x, and the unobservable components in υ_o,υ_s capturing the unobserved heterogeneity that is assumed to be gamma distributed. The MPH model allows for the simultaneous modeling of the two failures T_o,T_s. To ensure that the MPH framework is applied appropriately, we verify that the following assumptions have been met. Controlling for x and υ, we ensure that the shape of the hazard of an unemployment exit θ_o is not influenced by the hazard of a sanction unless a sanction occurs in T_s implying $\theta_o|t_s,x,\upsilon_o$ for $t_o > t_s$.

Unemployed in Germany are warned about the possibility of sanctions in case of non-compliant behavior, immediately after they have entered unemployment. These instructions about legal consequences are constantly repeated with every official letter that includes any request or invitation to the benefit recipient. Such permanent warnings, as well as explicit warnings of case managers who assess non-compliant behavior, can already cause so-called ex-ante effects.[36]

But our study focuses on the ex-post effects of sanctions. Nevertheless, we might expect a moderate change in behavior, immediately before a sanction is imposed, as the unemployed could expect that a sanction is going to be applied if she or he does not behave according to the compliance commitments. However, whether sanctions indeed are enforced, depends primarily on the case managers and how strict they follow the sanction regulations and whether they are willing to accept possible reasons that could justify the seemingly non-compliant behavior. Boockmann, Thomsen, and Walter, (2014) find that the probability to be sanctioned varies considerably across welfare

[36]The effects of (explicit) warnings are commonly referred to as ex-ante effects in the literature, see Lalive, Ours, and Zweimüller, (2005) and Arni, Lalive, and Ours, (2013). As outlined in Section 4.1, there are less than a handful of empirical studies analyzing the ex-ante effects of explicit warnings — they do indeed provide significant evidence of these effects.

agencies, according to their sanction policies which depend on the region, the entire economic situation that makes it either more or less difficult to find a job, regardless of the search intensity and the willingness to accept worse job conditions, and probably on the attitudes of the chief officers. Altogether, it is very difficult for the unemployed to assess whether they will be sanctioned, and additionally, they do not know the exact point in time, T_s, at which a possible sanction will be imposed. Following the argumentation of Abbring and Berg, (2003a) and Abbring and Berg, (2003b), we assume that the so-called no-anticipation assumption is satisfied. This assumption is important for our analysis in order to guarantee that individuals do not change their behavior before the treatment occurs.

Moreover, it is assumed that the unobserved heterogeneity is independent from the time-varying covariates in x. The independency and no-anticipation assumption ensures that the causal effect of a specific treatment on the hazard of exiting unemployment is identified by a MPH framework, hence conditional on the observed explanatory variables in x and the unobserved heterogeneity υ_o and υ_s. Therefore, selectivity is captured by the correlation between those two unobserved heterogeneity components υ_o and υ_s.

4.6 Results

For the analysis, we focus on two main hazard specifications: one for the exit to employment θ_e, the other for the exit to non-employment θ_{ne}. To avoid bias potentially arising from endogeneity of the sanction treatment, we model the duration until the sanction imposition as endogenous. All models are specified as discrete MPH models,[37] where hazards for both θ_e and θ_{ne} are estimated simultaneously.[38]

For our baseline models (Specification I) in Subsection 4.6.1, we assume the effect of a sanction as constant across the sample population. The impact of a sanction enters the unemployment hazard equation as a time-varying dummy variable δ, being 1 in t if a sanction already has been imposed, and zero otherwise. Besides δ, all models include a basic set of explanatory variables reflecting individual socio-economic characteristics, working motives and, to approximately capture general labor market conditions, a set of dummy variables for each federal state and the respective unemployment rate (uq). For the sensitivity analysis in Subsection 4.6.2, we allow the effect of a sanction to vary across the sample population. Hence, the expanded models (Specification II) let

[37] The episodes of (un-)employment are reported on a monthly frequency on a short observation period, so we use discrete MPH models.

[38] As mentioned in Section 4.5, we estimate the two processes as independent due to convergence problems of the likelihood function in a competing risk specification that otherwise would have been preferable.

δ interact with selected explanatory variables used before, and outlined in Table 4.2 of Section 4.4.

Finally, Submodels (a) and (b) differ with respect to the specification of the baseline hazard. Submodel (a) assume a log-linear combined with a log-quadratic impact of unemployment duration on the unemployment exit hazard (θ_e, θ_{ne}).[39] In contrast, Submodel (b) impose a piecewise-constant duration dependence as a more flexible approach in explaining how different unemployment periods might affect the exit to employment or non-employment.

4.6.1 Baseline Models

The results in Table 4.3 provide significant evidence of a positive impact (δ) of benefit sanctions on employment entry for Submodels (a) and (b). We find that sanctions enhance the transition to employment by 70% for the log-quadratic baseline hazard (a), and by 68% for the flexible piecewise-constant duration dependence (b).[40] Our results for the employment hazard are in line with the majority of previous German and other European studies that predominantly find positive effects of benefit sanctions on employment entry for UI and welfare recipients.[41]

It is worth emphasizing that the recent studies by far do not reveal the entire picture of the impact of, in particular, welfare sanctions as most studies focus on unemployment insurance sanctions. One potentially adverse effect of sanctions upon an increase in the exit rates from labor force is empirically found and presented in Table 4.3. We obtain strongly positive and significant evidence of benefit sanctions on the hazard out of labor force. Sanctions increase the transition rate to non-employment by 60% for the log-quadratic specification (Submodel (a)) and by considerable 79% for the piecewise-constant specification (Submodel (b)) of the baseline hazard. Hence, the estimated effects of benefit sanctions on exit from labor force, which, for UI recipients in Switzerland and Germany were found by Arni, Lalive, and Ours, (2013) and Hofmann, (2012),

[39] Although, the model is applied to discrete data, we estimate the parameters for a constant log-linear and log-quadratic impact of unemployment duration on the outflow hazard.

[40] For the estimation procedure we use the program *Sabre*. Besides others, *Sabre* has been developed for estimation of multivariate generalized linear mixed models, especially applied to discrete data and small data samples. One shortcoming is that the procedure does not report the estimated mass points for unobserved heterogeneity.

[41] Well-known recent European studies on UI recipients — mainly finding positive effects of benefit sanctions on employment entry — are provided by Berg and Vikström, (2014) for Sweden, by Busk, (2014) for Finland, by Arni, Lalive, and Ours, (2013) for Switzerland, and by Hofmann, (2012) for Germany (see Section 4.1). Most recent studies on welfare recipients — also finding positive effects of sanctions on employment entry — are provided by Klaauw and Ours, (2013) for the Netherlands, by Busk, (2014) for Finland, and by Boockmann, Thomsen, and Walter, (2014) and Berg, Uhlendorff, and Wolff, (2014) for Germany (see Section 4.2).

respectively, are also confirmed by this study for employable welfare recipients (i.e. UB II recipients) in Germany.

Apparently, there are two groups of UB II recipients which respond to sanctions differently: after a benefit sanction, one group reacts with a successful job search, to some extent by accepting worse employment conditions or/and by increasing the general search effort for jobs, whereas the other group becomes increasingly prone to exit the labor force, possibly driven by an increased search effort for alternatives to welfare receipt and employment[42]

The negative log-quadratic term of unemployment duration in the Model Ia in Table 4.3 reveal a non-linear relation between unemployment duration and the hazard to leave UB II receipt for employment θ_e respective non-employment θ_{ne}. Putting it differently, after a certain spell length, the probability of finding a job or leaving the labor market declines with ongoing UB II receipt.

Imposing the unemployment duration dependence as a flexible piecewise constant baseline function (Model Ib) in terms of four intervals ($[0-4);[4-7);[7-13);[13-37)$, in months) brings up positive and significant estimates for all three intervals (given $[0-4)$-interval as reference group). This holds for both hazards θ_e and θ_{ne}. The estimated coefficients are positive and significant but decline in the magnitude of their impact conditional on unemployment duration. In light of the inverse u-shaped duration dependence in the Model Ia for θ_e and θ_{ne}, the impact is supposed to turn negative for shorter interval setting in the end.[43]

A quick glance through Models Ia and Ib in Table 4.3 reveals the typical impacts of the explanatory variables on unemployment-to-employment hazard θ_e. Apart from the direction of the impact, almost all become statistically significant with some variations in the size of the coefficients between Submodels (a) and (b). The variables *migrated* and *couple*, and two variables of work motivation (*monetary* and *social*) turn out to be insignificant. Female, younger and elder UB II recipients, and unemployed UB II recipients in households with children below six years are less likely to enter employment. High- and medium-skilled unemployed, and unemployed reporting they are also motivated to work if they do not require the money ('*non-monetary* working motivation') have a higher likelihood to leave unemployment for employment. Apart from the sanction coefficient, also the significance of the explanatory variables is robust against continuous and discrete specification of duration dependence.

[42] As mentioned in Section 4.1, such alternatives include: living on the income of relatives and/or friends, student's assistance, disability pension, early retirement pay, illegal work or even criminal activity (Ames, (2009), Götz, Ludwig-Mayerhofer, and Schreyer, (2010), Machin and Marie, (2004), Røed and Westlie, (2012), Schreyer, Zahradnik, and Götz, (2012), and Wolff, (2014)).

[43] Due to the small sample size, we choose the parameters to estimate parsimoniously.

TABLE 4.3: Baseline models, Exit equations (θ_e and θ_{ne})

	Employment θ_e				Non-Employment θ_{ne}			
	Model Ia		Model Ib		Model Ia		Model Ib	
Variable	coef	z-stat	coef	z-stat	coef	z-stat	coef	z-stat
δ	0.528	2.45	0.520	3.75	0.469	2.04	0.583	3.44
lnt	0.285	1.69			0.972	4.01		
lnt^2	-0.121	-2.81			-0.237	-3.91		
d4–6			3.755	25.96			4.122	20.76
d7–12			2.692	19.74			3.438	19.75
d13–36			1.396	12.25			1.978	12.54
women	-0.591	-5.43	-0.454	-5.59	0.164	1.56	0.196	2.04
med skilled	0.613	4.65	0.394	3.65	0.341	2.66	0.050	0.45
high skilled	0.794	4.31	0.471	3.04	0.186	0.85	-0.175	-0.87
age24–	-0.540	-2.93	-0.698	-4.33	1.462	6.73	0.988	7.75
age50+	-1.168	-7.47	-0.751	-6.44	-0.031	-0.25	0.318	2.71
couple	-0.039	-0.36	-0.139	-1.48	0.840	6.08	0.603	5.88
child6	-0.338	-2.60	-0.186	-1.71	-0.262	-1.97	-0.093	-0.76
migrated	-0.083	-0.72	-0.024	-0.23	-0.220	-1.72	-0.158	-1.38
uq	-0.193	-6.69	-0.096	-5.06	-0.147	-5.00	-0.073	-3.23
non-monetary	0.366	2.70	0.280	2.39	-0.213	-1.65	-0.232	-1.98
monetary	-0.122	-1.31	-0.055	-0.67	-0.094	-0.91	-0.037	-0.40
social	0.021	0.14	0.089	0.68	0.257	1.51	0.272	1.76
regional dummies	yes		yes		yes		yes	
unobs. heterogen.[1]	yes		yes		yes		yes	

[1]Mass points for the terms of unobserved heterogeneity are estimated but not reported by *Sabre*, the program we used for the estimation procedure.

Considering Models Ia and Ib for the exit hazard to non-employment θ_{ne}, the estimated coefficients form a slightly different picture. Compared to the unemployment-to-employment hazard, θ_e, the impact of living with a partner in the same household (*couple*), being younger than 25 (*age24–*) and older than 49 (*age50+*) for Model Ib positively affects the hazard to non-employment. In other words, younger and elder (for Model Ib) unemployed UB II recipients are more likely to exit the labor market. With respect to duration dependence, we find the similar inverse u-shaped impact as for the exit hazard to employment, implying an increasing probability to remain unemployed after a certain length of the unemployment spell.

TABLE 4.3: Baseline models, Sanction equations (θ_s)

	Employment *e*				Non-Employment *ne*			
	Model Ia		Model Ib		Model Ia		Model Ib	
Variable	coef	z-stat	coef	z-stat	coef	z-stat	coef	z-stat
lnt	-0.351	-1.58	-0.350	-1.57	-0.350	-1.58	-0.334	-1.49
lnt^2	0.063	1.10	0.062	1.07	0.062	1.07	0.063	1.08
woman	-0.195	-1.63	-0.190	-1.60	-0.190	-1.59	-0.195	-1.64
med skilled	0.165	1.17	0.170	1.21	0.171	1.21	0.175	1.24
high skilled	0.051	0.20	0.076	0.31	0.077	0.31	0.090	0.36
age24–	0.253	1.37	0.271	1.48	0.272	1.48	0.278	1.52
age50+	-0.493	-3.16	-0.493	-3.18	-0.493	-3.18	-0.502	-3.24
couple	-0.009	-0.07	-0.014	-0.10	-0.013	-0.09	-0.008	-0.06
child6	-0.088	-0.59	-0.083	-0.55	-0.083	-0.55	-0.079	-0.53
migrated	-0.246	-1.65	-0.252	-1.69	-0.252	-1.69	-0.262	-1.77
uq	-0.076	-2.22	-0.076	-2.22	-0.076	-2.22	-0.071	-2.22
Log-Lik	-5551		-5221		-4828		-4519	
cases	3239		3239		3239		3239	
N	150204		150204		150204		150204	

Surprisingly, unemployment duration exhibits no significant effect on sanction probability (see Table 4.3). Moreover, people over 50 years of age (*age50+*) and *migrated* persons are less likely to be sanctioned, whereas the remaining factors turn out to be insignificant. Finally, the probability of experience a sanction increases with a declining regional unemployment rate *uq*, supporting common practice that job centers pursue a stricter sanction policy in regions with better economic conditions and a lower share of UB II recipients.

4.6.2 Sensitivity Analysis

We modify the baseline specification with selected interaction terms to analyze whether sanction effects with respect to age and education vary across different subgroups of the sample population. First, we let the dummy for being sanctioned δ interact with either age groups (*24–* and *50+*), and second with two qualification levels (*medium* and *high skilled*).

As shown in Table 4.4, we find strong evidence for a positive sanction effect on the exit hazard to employment θ_e. Considering interaction terms for the age groups, we find the transition to employment to be positively influenced by sanctions for either age cohorts. Apparently, younger than 25 or elder than 49 years old UB II recipients,

TABLE 4.4: Exit to employment θ_e

	2 Interaction Terms				4 Interaction Terms			
	Model IIa		Model IIb		Model IIa		Model IIb	
Variable	coef	z-stat	coef	z-stat	coef	z-stat	coef	z-stat
δ*med					0.396	1.97	0.296	1.63
δ*high					-0.105	-0.20	0.285	0.60
δ*age24–	0.834	1.79	1.097	2.51	0.733	1.56	1.010	2.29
δ*age50+	1.114	2.91	0.957	2.72	0.852	2.04	0.716	1.89
lnt	0.284	1.69			0.280	1.67		
$\ln t^2$	-0.123	-2.87			-0.123	-2.88		
d4–6			3.747	25.91			3.754	25.93
d7–12			2.696	19.76			2.696	19.74
d13–36			1.396	12.25			1.394	12.23
women	-0.586	-5.56	-0.468	-5.77	-0.578	-5.49	-0.458	-5.63
med skilled	0.608	4.77	0.412	3.82	0.576	4.51	0.385	3.52
high skilled	0.794	4.45	0.486	3.14	0.798	4.40	0.465	2.93
age24–	-0.596	-3.16	-0.789	-4.65	-0.586	-3.12	-0.782	-4.60
age50+	-1.229	-7.94	-0.826	-6.82	-1.207	-7.80	-0.807	-6.62
couple	-0.041	-0.39	-0.144	-1.54	-0.037	-0.36	-0.140	-1.48
child6	-0.329	-2.59	-0.190	-1.74	-0.324	-2.55	-0.187	-1.72
migrated	-0.084	-0.75	-0.023	-0.23	-0.081	-0.72	-0.026	-0.25
uq	-0.193	-6.82	-0.100	-5.29	-0.191	-6.76	-0.098	-5.17
non-monetary	0.365	2.74	0.293	2.50	0.356	2.68	0.285	2.42
monetary	-0.118	-1.30	-0.055	-0.67	-0.120	-1.31	-0.053	-0.65
social	-0.001	0.00	0.070	0.53	0.005	0.03	0.079	0.60
regional dummies	yes		yes		yes		yes	
unobs. heterogen.[1]	yes		yes		yes		yes	

[1]Mass points for the terms of unobserved heterogeneity are estimated but not reported by the program *Sabre*.

affected by a sanction are more likely to enter employment, whereas in general these age groups are associated with a lower transition probability.

The interaction with qualification levels in the Models IIa and IIb reveal a slightly changed picture as the impact of sanctions on the age group of 'young adults' (*24–*)becomes insignificant. For older unemployed UB II recipients, the transition rate to employment remains positively affected by sanction enforcements. The general positive effect of education on the transition probability to employment becomes insignificant

TABLE 4.4: Sanction equation θ_e

	2 Interaction Terms				4 Interaction Terms			
	Model IIa		Model IIb		Model IIa		Model IIb	
Variable	coef	z-stat	coef	z-stat	coef	z-stat	coef	z-stat
lnt	-0.350	-1.57	-0.350	-1.57	-0.350	-1.57	-0.350	-1.57
lnt^2	0.062	1.07	0.062	1.07	0.062	1.07	0.062	1.07
woman	-0.190	-1.60	-0.190	-1.60	-0.190	-1.60	-0.190	-1.60
med skilled	0.170	1.21	0.170	1.21	0.170	1.21	0.170	1.21
high skilled	0.076	0.31	0.076	0.31	0.076	0.31	0.076	0.31
age24–	0.271	1.48	0.271	1.48	0.271	1.48	0.271	1.48
age50+	-0.493	-3.18	-0.493	-3.18	-0.493	-3.18	-0.493	-3.18
couple	-0.014	-0.10	-0.014	-0.10	-0.014	-0.10	-0.014	-0.10
child6	-0.083	-0.55	-0.083	-0.55	-0.083	-0.55	-0.083	-0.55
migrated	-0.252	-1.69	-0.252	-1.69	-0.252	-1.69	-0.252	-1.69
uq	-0.076	-2.22	-0.076	-2.22	-0.076	-2.22	-0.076	-2.22
regional dummies	yes		yes		yes		yes	
Log-Lik	-5553		-5222		-5551		-5221	
cases	3239		3239		3239		3239	
N	150204		150204		150204		150204	

for high-skilled and for medium-skilled unemployed in Model IIb. On average, the transition probability of high-skilled unemployed seems to be unaffected by sanctions. To sum up, sanction effects do vary in its impact across different age cohorts of the sample population.

Focusing on sanctioned unemployed UB II recipients with regard to their qualification level, the model does not indicate any significant impact of sanctions on high skilled unemployed. For medium qualified persons, Model IIa with the log-quadratic specification (Submodel (a)) indicates a significantly positive effect of sanctions on the transition to employment.

Concerning the hazard to non-employment in Table 4.5, the results for the medium skilled sanctioned appear robust against the two different baseline hazards. Here, sanctions on medium-skilled unemployed robustly facilitates the transition to non-employment, whereas the insignificant effect of sanctions on high-skilled unemployed resembles the results found for the hazard to employment in Table 4.4.

In summary, sanction effects do not only vary across different age cohorts but also across different qualification levels. The results of a general positive impact of sanctions on transition out of unemployment, as obtained by the baseline models presented in Table 4.3, are only partially verified by the models, controlling for interaction effects. Put

TABLE 4.5: Exit to Non-Employment θ_{ne}

	2 Interaction Terms				4 Interaction Terms			
	Model IIa		Model IIb		Model IIa		Model IIb	
Variable	coef	z-stat	coef	z-stat	coef	z-stat	coef	z-stat
δ*med					0.498	1.90	0.526	2.20
δ*high					-1.161	-1.09	-0.175	-0.17
δ*age24–	0.445	1.23	0.766	2.39	0.349	0.97	0.654	2.01
δ*age50+	1.171	3.37	1.037	3.39	0.905	2.24	0.687	1.93
lnt	0.974	4.02			0.968	4.00		
$\ln t^2$	-0.237	-3.92			-0.238	-3.97		
d4–6			4.119	20.72			4.126	20.73
d7–12			3.442	19.77			3.442	19.75
d13–36			1.975	12.52			1.973	12.49
women	0.162	1.52	0.188	1.95	0.168	1.60	0.201	2.08
med skilled	0.346	2.69	0.055	0.49	0.306	2.39	0.009	0.08
high skilled	0.195	0.89	-0.169	-0.84	0.252	1.15	-0.174	-0.85
age24–	1.442	6.76	0.922	7.04	1.439	7.01	0.931	7.09
age50+	-0.113	-0.87	0.237	1.97	-0.093	-0.72	0.266	2.18
couple	0.847	6.15	0.604	5.89	0.845	6.32	0.608	5.91
child6	-0.267	-1.99	-0.099	-0.81	-0.262	-1.97	-0.090	-0.73
migrated	-0.227	-1.77	-0.150	-1.30	-0.220	-1.73	-0.148	-1.28
uq	-0.150	-5.08	-0.076	-3.39	-0.147	-5.06	-0.074	-3.30
non-monetary	-0.217	-1.68	-0.219	-1.86	-0.226	-1.76	-0.229	-1.95
monetary	-0.090	-0.87	-0.036	-0.38	-0.093	-0.91	-0.034	-0.36
social	0.253	1.48	0.265	1.70	0.254	1.50	0.277	1.78
unobs. heterogen.[1]	yes		yes		yes		yes	

[1]Mass points for the terms of unobserved heterogeneity are estimated but not indicated by the program *Sabre*.

differently, even if benefit sanctions on average facilitate the flow out of UB II receipt across the estimation sample, the impact on the behavior within distinct sub-groups may be ambiguous. So far, we find no evidence for a contradicting effect, for example that sanctions on young UB II recipients exhibit a positive impact of the transition to employment, whereas the effect upon older UB II recipients turns out to be negative. In particular, the transition of unemployment to employment or out of the labor force within different sub-samples of welfare recipients entails different, and probably inconsistent, sanction effects. Unfortunately, the small sample size does not allow a more

TABLE 4.5: Sanction equation θ_s

	2 Interaction Terms				4 Interaction Terms			
	Model IIa		Model IIb		Model IIa		Model IIb	
Variable	coef	z-stat	coef	z-stat	coef	z-stat	coef	z-stat
lnt	-0.350	-1.57	-0.350	-1.57	-0.350	-1.57	-0.350	-1.57
lnt^2	0.062	1.07	0.062	1.07	0.062	1.07	0.062	1.07
woman	-0.190	-1.60	-0.190	-1.60	-0.190	-1.60	-0.190	-1.60
med skilled	0.170	1.21	0.170	1.21	0.170	1.21	0.170	1.21
high skilled	0.076	0.31	0.076	0.31	0.076	0.31	0.076	0.31
age24–	0.271	1.48	0.271	1.48	0.271	1.48	0.271	1.48
age50+	-0.493	-3.18	-0.493	-3.18	-0.493	-3.18	-0.493	-3.18
couple	-0.014	-0.10	-0.014	-0.10	-0.014	-0.10	-0.014	-0.10
child6	-0.083	-0.55	-0.083	-0.55	-0.083	-0.55	-0.083	-0.55
migrated	-0.252	-1.69	-0.252	-1.69	-0.252	-1.69	-0.252	-1.69
uq	-0.076	-2.22	-0.076	-2.22	-0.076	-2.22	-0.076	-2.22
regional dummies	yes		yes		yes		yes	
Log-Lik	-4825		-4516		-4822		-4514	
cases	3239		3239		3239		3239	
N	150204		150204		150204		150204	

differentiated analysis.

4.7 Conclusion

In this paper, we have analyzed the impact of benefit sanctions on transition rates from unemployment into two distinct outcomes: employment and non-employment. In contrast to the majority of European studies on benefit sanctions, we focused on employable welfare recipients, in Germany recipients of the UB II, instead of recipients of unemployment insurance benefits. Unlike previous studies — and due to the regulations that UB II is not granted individually but paid to the entire household — we assumed and treated all employable household members of a so-called ‘need unit’ as affected. On average, the labor market prospectives of welfare recipients are worse than for UI recipients, so that leaving benefit receipt for non-employment appears as a more appealing option for them than for UI recipients.

Based on a Mixed Proportional Hazard (MPH) model which treats sanctions as endogenous, we actually identified two distinct effects: unemployed UB II recipients that become affected by a sanction are more likely to enter employment, but are also more likely to leave the labor market, at least temporarily. With our analysis we provide causal evidence that the positive effect of benefit sanctions on employment entry of welfare recipients is at expense of a likewise increased probability to get them off the labor market. In other words, there are two groups of unemployed welfare recipients that respond to benefit sanctions differently. Whereas one group of sanctioned individuals on average exhibit increasing transition rates to employment, the other group becomes more likely to leave the entire labor force. According to job search theory, the positive effect of benefit sanctions on the transition to employment is supposed to arise from enhancing job search efforts and from accepting worse job conditions. Thus, the increased transition rate to employment might be at expense of job quality in terms of lower wages and lower job stability (Arni, Lalive, and Ours, (2013)). On the oder hand, the increased probability for an exit from labor force is likely driven by an intensified search for alternatives to welfare receipt and employment.

At first glance, the findings of an increased impact on transition out of unemployment coincides with the policy intentions — at least the short-term ones — that predominantly aim to reduce the duration and amount spent on welfare in order to lower both unemployment rates and fiscal costs. Here, welfare policy that aims to push people into employment at any price might be accompanied by a downgrade in occupational skills, unstable employment and low wages, even below the subsistence level. In the long-run, the latter potentially leads to the opposite of the policy's intended outcomes — increased durations of (supplementary) welfare receipt for more and more individuals, and hence increased expenditures for welfare payments.

In the end, future research should target the examination of such likely negative effects to obtain a comprehensive evaluation of the impact of benefit sanctions that goes beyond public labor market policy that merely aims to bring people as quickly as possible from benefit receipt into employment.

Chapter 5

Rule-based Modeling of Labor Market Dynamics: An Introduction

This chapter is based on Kühn and Hillmann, (2014)

5.1 Introduction

Mathematical models are increasingly used as formal descriptions of real world systems and employed to analyze the dynamics of these systems. Classical mathematical descriptions (e.g. differential equations) use continuous variables to describe aggregate numbers that emerge from an underlying population. An example from economics is a group of persons, e.g. unemployed or employed in a certain industry sector, described by continuous variables. One of the assumptions underlying this kind of description is that the individuals in the population are, at least to a certain degree, homogeneous.

This assumption is rarely true. The importance of accounting for this invalid assumption is recognized in the emergence of mathematical frameworks that describe the heterogeneity of populations by explicitly modeling the individual agents that constitute the population. Those more complex frameworks, required to describe socio-economic systems, are commonly referred to as agent-based models (ABM).

Agent based frameworks are a class of very divergent algorithms and tools, ranging from educational frameworks like Netlogo (Wilensky, 1999) to java-based general purpose simulators frequently used in economics like Repast (North et al., 2013) and MASON (Luke, Cioffi-Revilla, and Panait, 2005) to frameworks designed to host large-scale projects like FLAME (Coakley et al., 2012), among many others. As diverse as are the tools, as diverse is their application both in economic (Dawid and Neugart, 2011) and biological (Kirschner and Linderman, 2009; Tokarski et al., 2012; Li et al., 2013) research. As distant as socioeconomic and biological modeling might seem, the underlying algorithms and tools are similar, as the examples of Netlogo and FLAME show.

Here, we introduce rule-based modeling, a subclass of agent based modeling with a strong formal background, to the analysis of socio-economic problems. In biological modeling, the rule based frameworks BioNetGen (Sneddon, Faeder, and Emonet, 2011) and κ (Danos et al., 2007) have been used both for modeling (Pincus et al., 2013; Creamer et al., 2012) and as an engine for collecting knowledge and constructing models (Lopez et al., 2013; Tiger et al., 2012; Kühn et al., 2010). Its strong formal foundation also gives rise to different methods of model analysis (e.g. using stories in κ (Vincent Danos and Krivine, 2008)) and conversion to deterministic ODE-models (Feret et al., 2009) or hybrid models (Hogg et al., 2014). On the other hand, RBM frameworks are less versatile than the java-based general purpose simulators: they do not consider spatial dimensions and are yet limited in their ability to describe continuous variables.

The remainder is as follows: This section gives an overview of ABM applied to labor market studies, followed by a detailed introduction of RBM and its syntax. In Section 5.2, we describe a simple model of labor market dynamics and its comparison to Netlogo and MASON implementations. We conclude with a discussion of the advantages and disadvantages of RBM and an outlook in Section 5.3.

5.1.1 Agent Based Modeling of Labor Market Dynamics

General literature on the motivation of ABM and its chronological discussion is provided by (Colander et al., 2008; Kirman, 1992; Tesfatsion, 2006a; Tesfatsion, 2006b; LeBaron and Tesfatsion, 2008; Dawid and Fagiolo, 2008; Dawid and Neugart, 2011). Recently, Neugart and Richiardi, (2012) contributed a comprehensive survey of agent-based labor market models.

Since the beginning of 2000, the field of ABM of employer-employee networks has started to emerge, primed by the articles of Tesfatsion on adaptive behavior in evolutionary labor markets (Tesfatsion, 2000; Tesfatsion, 2001) and the emergence of structural employer-employee networks (Tesfatsion and Pingle, 2003). These studies investigate the engagement process of both work suppliers and employers, modeled as prisoner's dilemma game, in finding the most preferable worksite partner conditional on regularly updated expected utility. The study aims to explain how labor market institutions, in particular unemployment benefits, affect the decision to work or not to work, and in turn the level of unemployment. More specifically, effects of an increased job capacity or job concentration on a change in aggregate and disaggregate market power for work suppliers and employees is evaluated.[1]

[1] In parallel to the agent-based model, a human subject experiment was conducted to verify the results of the computational experiment.

Fagiolo, Dosi, and Gabriele, (2004) develop an agent-based, evolutionary worker-firm matching model, featuring bargaining behavior with regard to wages proposed by firms and accepted or rejected by workers. Production starts after the matching process has been finished. Firms making negative profits exit the market, being replaced by entrants. A study by Richiardi, (2006) deals with the simulation of an agent-based labor market model built on transition processes reflecting the decisions made by firms, workers and also entrepreneurs. Similar to Fagiolo, Dosi, and Gabriele, (2004), he robustly replicates stylized facts, such as Beveridge, Wage and Okun curves. By the implementation of shocks, Richiardi, (2006) explores the out-of-equilibrium dynamics and finds rather limited evidence for the stylized facts that do emerge while the economy is in steady state.

Using *RePast*, Neugart, (2008) employs an agent-based model to examine the aggregate impact of government training subsidies in Germany on an individuals probability to find a job given that other job-searchers are to some degree disadvantaged by not receiving governmental support. Gemkow and Neugart, (2011) focus on the impact of referral hiring in worker-firm matchings on the incidence of unemployment. They find that the importance of social contacts decreases in favor for a higher volatility in labor demand if labor markets are less tight. In fact, the probability of entering or exiting unemployment becomes rather independent from social network structure.

These examples highlight the importance that agent based models currently have in developing and testing new hypotheses on labor market dynamics, but they also highlight a frequent dilemma of agent based models: the models are often not publicly available and if they are, they consist of hundreds of lines of source code, the reusability of which is often strongly determined by the authors coding style.

5.1.2 Rule Based Modeling

One of the main functional units of molecular biology are proteins that catalyze reactions or interact to transduce information. Proteins interact with each other, often forming large complexes. Within these complexes, each individual protein can be in different states of activity which in term influence the overall activity of the complex. If all possible states are accounted for, this quickly leads to an explosion of the state space: a full description of the interactions of seven proteins in a well studied signaling cascade would require up to 1900 state variables if represented as ODEs (Kühn et al., 2010). The emergence of detailed and high throughput data have led to the recognition of the importance of this complexity (Bray, 2003), especially in the crosstalk of different signaling pathways (Waltermann and Klipp, 2010; Kholodenko, 2006).

Based on the observation that this complexity cannot be encoded in classical ODE modeling, new modeling frameworks were adapted to the use in biology starting in the early 2000s (Hlavacek et al., 2003). One of the first applications of rule based modeling to biological systems was introduced by Shapiro and coworkers (Regev, Silverman, and Shapiro, 2001; Priami et al., 2001) based on the π-calculus.

In RBM, systems are not represented as a set of variables and equations but as a set of rules that determines state changes in agents. Different algorithms exist for simulating rule based models, as discussed below. The key advantages of using RBM are

- an unambiguous and compact representation,
- the faithful description of systems with a large state space,
- that the state space of the described system is not required to be explicitly enumerated by state variables.

The π-calculus is a process algebra developed for the description of computer processes and specifying concurrent computational systems (Milner, Parrow, and Walker, 1992a; Milner, Parrow, and Walker, 1992b). Interactions between entities in this language are always binary interactions, e.g. an interaction is always between two entities. An extension, the stochastic π calculus (Priami, 1995), enables simulation of continuous time Markov chains.

Other approaches and respective implementations soon followed. Here, we use BioNetGen (Hlavacek et al., 2006), the syntax of which is almost identical to that of κ (Danos et al., 2008). But while the κ language is based on the process of communicating systems (Danos and Krivine, 2007), BioNetGen is based on graph rewriting rules (Blinov et al., 2006) and uses an extension of the approach used in κ for simulation (Yang et al., 2008). In addition, BNG models can be simulated using nfsim (Sneddon, Faeder, and Emonet, 2011), which implements a rule based version of Gillespies algorithm (Gillespie, 1976): The probability of executing each rule is computed from the current system state, the time to the next execution is sampled and an according rule is selected and executed, the system state is updated and the loop closes by updating the probabilities. This algorithm scales linearly with the number of rules and agents and is independent of the number of state variables, giving it an advantage in performance when simulating complex systems with many different interaction sites (Sneddon, Faeder, and Emonet, 2011). Other tools for RBM are described in Meier-Schellersheim et al., (2006), Moraru et al., (2008), Colvin et al., (2009), Colvin et al., (2010), and Andrews et al., (2010).

The rule based approach has been successfully applied to modeling biological systems and analyzing their dynamic properties (Lee et al., 2003; Ghosh et al., 2011; Thomson et al., 2011). Detailed quantitative predictions on individual pathways and experimental testing thereof have been limited so far, in part because some of the parameters introduced in these detailed models are difficult to assess experimentally.

Because rule based models are compact and unambiguous representations of a system, they have also been used to compile knowledge on signaling pathways (Tiger et al., 2012) and for creating models as programs (Lopez et al., 2013).

The demands on biological modeling tools certainly differ from the demands on tools for modeling socio-economic interactions, but we will show in the following that some of the advantages of RBM can be readily exploited for socio-economic modeling.

5.1.3 BioNetGen Language

BioNetGen and κ are two prominent RBM languages sharing a very similar syntax. We shortly introduce the BioNetGen syntax (or BioNetGenLanguage, BNGL) here. The κ syntax differs in the use of dots and plus signs in writing rules, but the general syntactic principles are identical.

In BNGL, models consist of a set of agents, a set of rules that define interactions between agents, initial conditions, a set of observables that monitor agent states during simulation, and possibly a set of functions that determine rule execution probabilities.

An agent in BNGL consists of a name and sites in brackets. In socio-economic terms, sites can be interpreted as attributes or individual characteristics, for example,

```
Person(Edu,Age,EMP)
```

defines an agent `Person` with attributes `Edu` and `Age` corresponding to education and age. The attribute `EMP` is an interaction interface we will use shortly.

Each site can be assigned one of a set of discrete states, denoted by

```
site~state.
```

For example, a `Person` with college degree could be specified as

```
Person(Edu~college).
```

Agents engage in binary interactions via sites denoted by

```
site!X
```

where `X` is an index of the interactions. A `Person` bound to some `Job` can be described as

```
Person(EMP!1).Job(EMP!1).
```

Each binary interaction consists of two binding partners, so each `!X` requires exactly one other `!X` on another agent, where `X` corresponds to an integer index.

Interactions among agents and changes in the state of a site are defined via rules. A rule comprises a name, a left and a right hand side, describing the state of the partaking agents before and after the execution of the rule, respectively, and a parameter that determines the probability that the given rule is executed.

Say an agent `Person` can engage in an interaction with an agent `Job` as described above (i.e. become employed in that job) with probability `p`. This interaction (employee-job match) is given by the rule

```
'StartEmp' Person(EMP) + Job(EMP) ->
    Person(EMP!1).Job(EMP!1) p.
```

The parameter `p` used in rules is defined analogous to parameters in mass action kinetics so that the mean rate r a rule is executed with is

$$r = p \cdot \prod_{n=1}^{k} agents(n), \tag{5.1}$$

where $agents(n)$ are the numbers of agents $n = 1, ..., k$ satisfying the left hand side of the rule. The careful reader has noticed that we have omitted those attributes of agents (`Age,Edu`) that are not relevant in the given example. This is an advantage of BioNetGen and κ, termed the 'don't care don't write' principle: any attribute omitted in specifying a rule or observable are ignored and can take any state. In this way, complex assemblies of agents can be formed using only simple rules.

The observables are the readout of the model: Here, one specifies which agents or agent assemblies in which state should be recorded during simulation.

In addition to fixed parameter settings to determine rule execution, nfsim enables the user to endogenize the probabilities by specifying a function of observables. As observables are recorded after each iteration step, probabilities do adapt to changes in the entire economic system. Handling these is not always trivial and reduces simulation speed but it opens up new options, for example to compute a global price function depending on aggregate supply and demand in the economy and use this for computing rule execution probabilities with respect to production. Another examples will be presented with the introduction to our simple model.

5.2 Results

5.2.1 A simple RBM model Reproduces Labor Market Dynamics

Here, we will exemplify the use of RBM for the description of socio-economic processes by a simple labor market model that can be readily extended. The main intention of this model is to demonstrate the feasibility of applying RBM to reproduce and describe general labor market dynamics. Due to the simplicity of the model, not all advantages of RBM are fully exploited.

To put it briefly, the labor market comprises companies, employed and unemployed persons. As standard in matching models, companies announce vacancies and unemployed persons apply for it, followed by a successful worker-company match. If no matching takes place, the job position remains vacant. Both vacant and occupied job position, however, are likely being withdrawn from the market by a given probability. In case of a separation, the job becomes vacant for a new worker-company match.

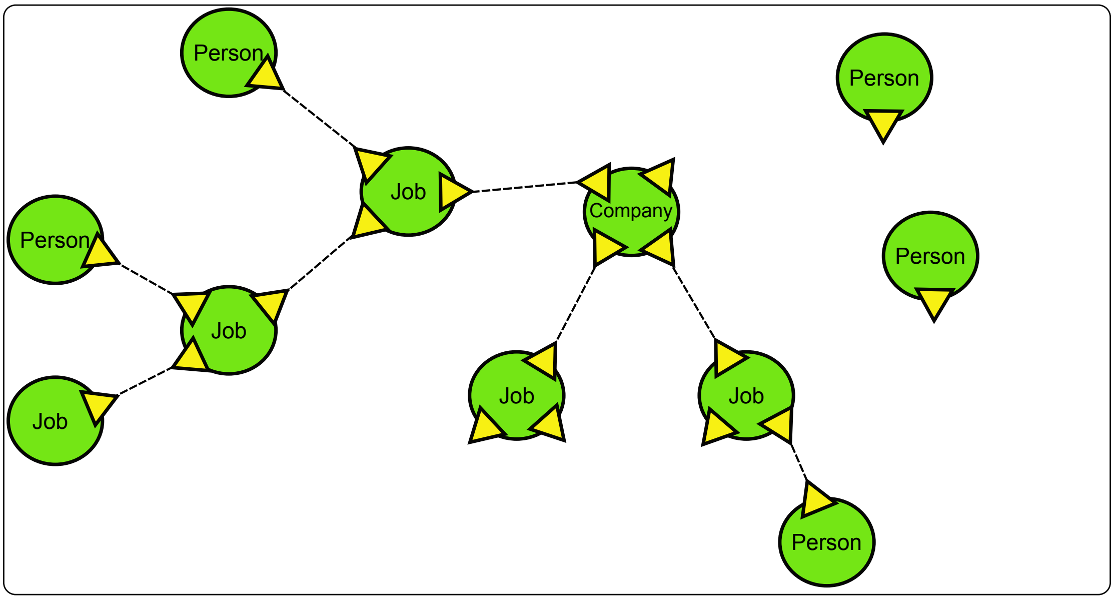


FIGURE 5.1: Illustration of a possible state of the labor market model: 1 company with 5 job position (2 vacancies, 3 occupied jobs) and 2 unemployed persons. Agents are visualized as green circles, interaction interfaces are indicated by yellow triangles. Interactions are indicated by dashed lines. Internal variables of the agents are omitted for clarity.

In BioNetGen terms, the model contains `Company` agents that anchor four chains of `Jobs`. A `Job` can interact with a `Person`-agent. Vacant `Jobs` at the end of the `Job`-chain are likely to vanish, `Jobs` interacting with `Persons` are likely to extend the chain of `Jobs` by appending an additional `Job` to itself. Upon separation, the `Person` becomes unemployed immediately, while the `Job` becomes vacant with a slight delay. An illustration of a possible state of this model is given in Figure 5.1. The complete model including rules, parameters, initial conditions and observables in BNGL syntax is given in the appendix.

For the implementation of this model in BioNetGen, we need three agents with particular attributes: One company given by `Company(j1,j2,j3,j4)` (where `j1`, `j2`, `j3`, `j4` are interaction sites for `Jobs`), jobs defined as `Job(l,r,e)` (where `l` and `r` are interaction sites for `Jobs` left and right in the `Job`-chain and `e` is the interaction site for `Persons` in an employment relation) and persons, `Person(EMP)` (where `EMP` is the interaction site for employment relations).

TABLE 5.1: Execution Probabilities `p`. u indicates unemployed and v vacancies.

Parameter	Interpretation	Value
μ	matching efficiency	1
β	returns to scale	0.9
`pJoJ`	job opening rate ('**J**ob **o**ffers **J**ob')	0.01
`pPgJ`	hiring rate ('**P**erson **g**ets **J**ob')	$\mu\frac{1}{u^{1-\beta}v^{\beta}}$
`pPlJ`	separation rate ('**P**erson **l**ose **J**ob')	0.04
`p_init`	initial population	1000

In this example of a Job-chain model, one `Company` can, given enough `Persons`, seed an infinitely growing chain of `Jobs`: A `Job` at the end of a given `Job`-chain (`Job(l!+,r)`) can seed another job via the rule `'Job offers job'` given that it is occupied by a `Person`. `'Job vanishes'` describes the deletion of a vacant Job at the end of the chain (`Job(e,r)`, indicating `e`, `r` are not occupied). The rules `'Person gets job'` and `'Person lose job'` describe employment and separation processes. The rule for worker-company matching is specified endogenously. A Cobb-Douglas production function given by $m = \mu u^{\beta} v^{1-\beta}$ is used to proxy the matching process and its execution probability. According to equation 5.1, with the mean rate r as the number of matches m and unemployed u and vacancies v as observables, the execution probability p is then derived by

$$p = \mu\frac{1}{u^{1-\beta}v^{\beta}}, \tag{5.2}$$

with μ as matching efficiency and β as returns to scale. As initial conditions, we use 1000 `Person(EMP)` and 10 Companies offering 4 jobs. We set model parameters to reproduce economic indicators (unemployment and vacancy rates, labor market tightness). These parameters are listed in Table 5.1. We run the model with these parameters 50 times over 200 iterations. As the model is calibrated to target monthly fluctuations, each iteration step is interpreted as one month.

The seminal paper by Shimer, 2005 evaluates the performance of the Mortensen-Pissarides search and matching equilibrium model (Mortensen and Pissarides, 1994; Pissarides, 2000) in reproducing unemployment-vacancy dynamics, in particular the large volatility observed for both aggregate variables. Although the model successfully predicts the strongly negative long-term relationship between unemployment and vacancies and the persistence in terms of autocorrelations, it falls short in replicating the volatile behavior captured by the standard deviation entailed by business cycle movements caused by shocks.[2] As Shimer, (2005) focuses on the cyclicality, he reports all variables, summarized as monthly averages per quarter, in logs as deviations from a HP-filtered trend with smoothing parameter 10^5. Here, we will adopt this to facilitate a comparison of our results with the findings by Shimer, (2005).

One realization of our model is depicted in Figure 5.2, corresponding summary statistics for 50 realizations are provided in Table 5.2. With an average unemployment rate of 4% , and a vacancy rate of 2%, the model produces reasonable values, yielding a labor market tightness of 0.5. Compared with (Shimer, 2005) our model generates a more volatile behavior of all variables, although it slightly overshoots for vacancies and labor market tightness. Although our fairly simple model is not able to produce the large persistency, it confirms a negative correlation of -0.663, and hence the typical negative slope of the Beveridge Curve. The strong positive correlation between hiring rate and labor market tightness (v/u) also closely resembles empirical data.

Stochastic simulations of this simple model reveal that, due to stochastic fluctuations, the system undergoes phases with few unemployed and many free jobs as well as phases with many unemployed and few free jobs, analogous to boom and depression phases in reality.

Most real life socio-economic systems are exposed to perturbations of various kinds that need to be accounted for in realistic models. In BioNetGen, perturbations can be introduced by simulating for a set time interval, recording the model state and restarting a model with modified parameters using the previous state as initial conditions. [3] We induce depressions by modifying the execution probability for separation `pP1J`. After 2000 timesteps with basic parameterization, we simulate the model with doubled `pP1J` (`pP1J` $= 0.08$) for 50 timesteps, followed by a relaxation period of 200 timesteps with basic parameterization followed by 50 timesteps with `pP1J` $= 0.02$ followed by 150 timesteps with basic parameterization.

[2] Since then, numerous studies followed to assess the 'Shimer Puzzle' and develop a model that overcomes the difficulties in properly explaining the cyclical unemployment-vacancy volatility.

[3] Here, κ provides more elegant means to introduce such perturbations to a model via a specialized syntax.

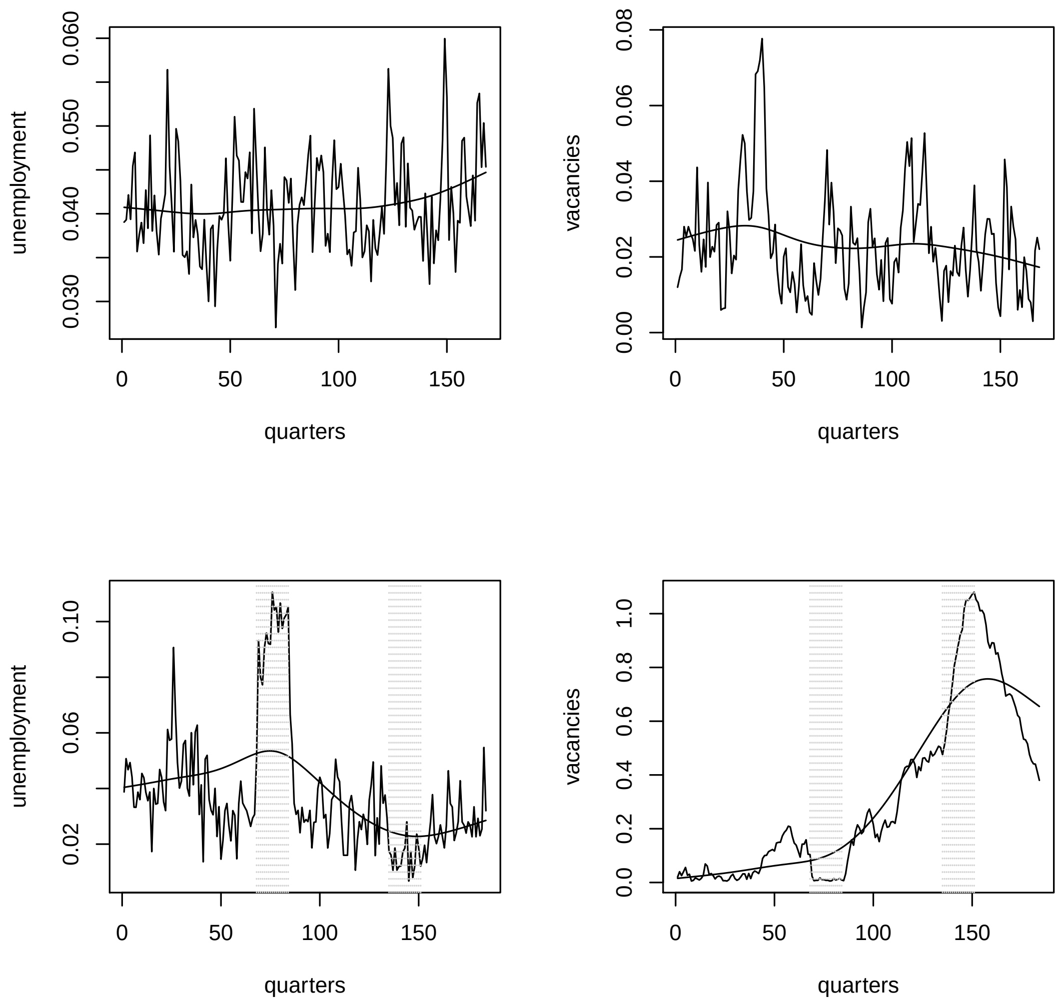


FIGURE 5.2: Unemployment and vacancy rates for representative model realizations, time given in quarters. The upper panels show fluctuations over time and a HP-filtered trend with smoothing parameter 10^5 for the unperturbed model. The lower panels show fluctuations obtained by two types of separation shock indicated in gray. More details on the shocks are provided by the text.

The lower panel of Figure 5.2 depicts one realization of the perturbed model. The shaded areas mark the segregation shocks. The doubled separation rate entails a sharp increase in unemployment from 3% up to 10%. However, unemployment returns to its equilibrium level of 3% with the same autocorrelation after the shock vanished. The vacancy rate decreases to 1% after a sharp increase to nearly 20% not induced by a implemented perturbation. Apparently, after the separation probability is reset to 4%, vacancies increase slowly but remarkably. Here, the vacancy rate did not return to the initial equilibrium level before the second shock starts. Moreover, the second shock of a lower separation rate amplifies the increase, entailing a vacancy rate of 100% for a

	u	v	θ	h	s
sd.deviation	0.147	0.772	0.874	0.144	0.096
autocorrelation	0.483	0.81	0.821	0.264	-0.089
v	-0.663***				
θ	-0.747***	0.991***			
h	-0.829***	0.569***	0.638***		
s	0.567***	-0.153*	-0.225***	-0.235***	

TABLE 5.2: Standard deviations, autocorrelation and cross-correlations of unemployment (u), vacancies (v), v/u-ratio (θ), hiring (h) and separation (s) rates for the baseline model without perturbations. All variables are reported in logs as deviations from the HP trend with smoothing parameter $\lambda = 10^5$. Except for v and θ, the standard deviations are remarkably close to empirical data. The persistent behavior in terms of autocorrelation of u, h and s is rather small compared to empirical data and results of Shimer, (2005).

short time. Thereafter, the vacancy rate decreases steadily.

In this model, we implemented only a few rules with respect to labor demand and abstained from describing wage setting and bargaining behavior on both sides. Although simple, our model reproduces a large amount of the persistent and volatile behavior of vacancies (v), unemployed (u), hiring rate (h) and separation rate (s), which these variables exhibit in reality (Table 5.2). The four plots in Figure 5.2 show the typical acyclical movements of vacancies and unemployed with associated negative correlation coefficients of -0.663 for the model without and -0.52 after the first shock (Table B.1 in the Appendix) and an insignificant coefficient of -0.136 after the second shock (Table B.2). This negative relationship between vacant job positions and unemployed over time - the Beveridge Curve - is visualized in Figure 5.3.

Even though the autocorrelations, in particular for the unemployment rate, are smaller than the simulated autocorrelations in Shimer, (2005), the standard deviations are remarkably close to the empirical data regardless of the presence of shocks. However, the job-search model of Shimer, (2005) with both productivity and separation shock, provides standard deviations less than 0.04, thus considerably smaller than the deviations in the data. Here, our model is able to replicate the existing volatility of unemployment and vacancies in the labor market. Furthermore, the cross correlations fairly exhibit the prevalent relationships between the variables.

Appendix B.1 provides the summary statistics and autocorrelations of unemployed, vacancies, labor market tightness, hiring and separation rate after the first and after the second shock. Again, while the rule-based model reproduces large standard deviations for unemployed, vacancies, labor market tightness, hiring and separation rate

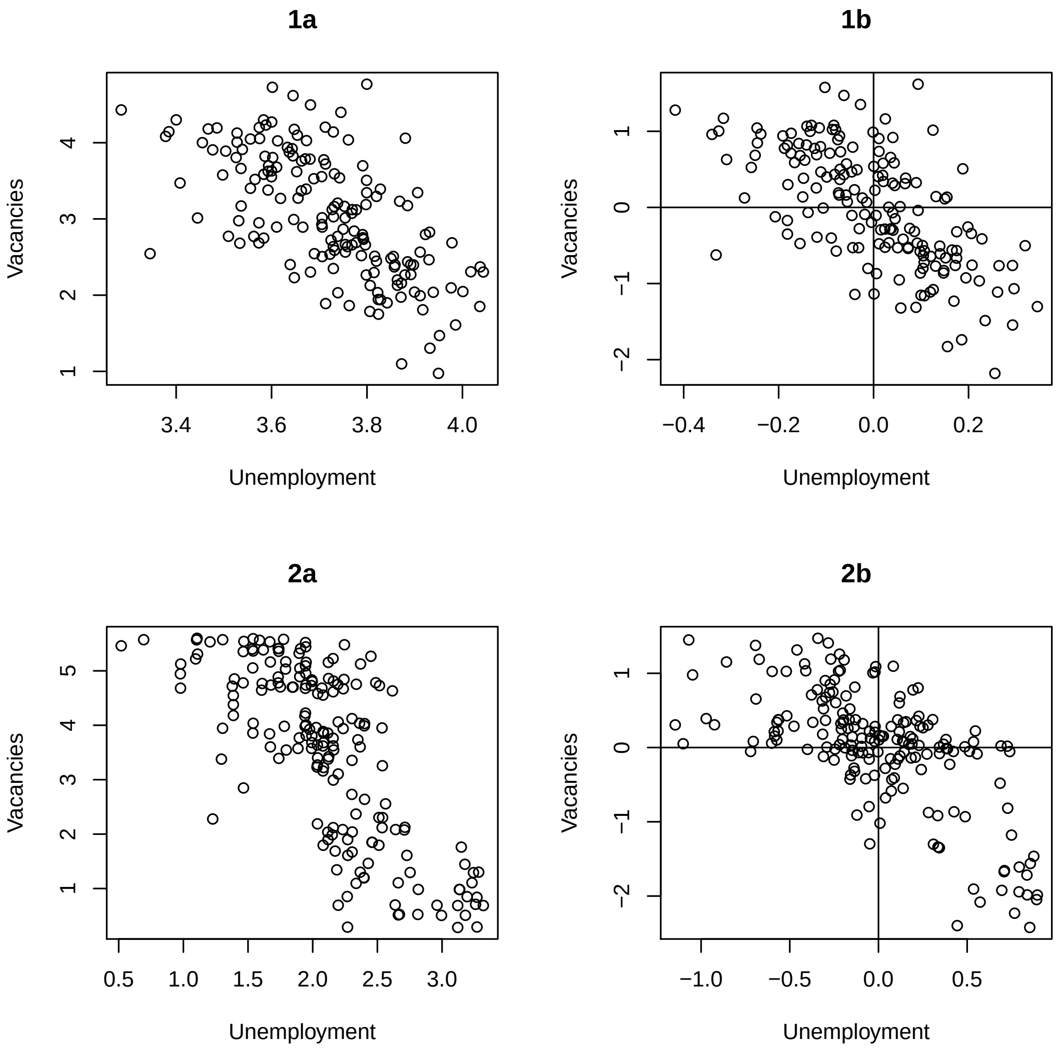


FIGURE 5.3: **The Beveridge Curve** (BC) or the v-u-ratio displays the trade-off between unemployed (u) and vacancies (v). Plots 1a and 2a show the v-u ratio in log-levels, 1b and 2b as log deviations from a HP-filtered trend. Plots 1a and 1b are obtained from the baseline model, 2a and 2b from the perturbed model. The v-u-ratio based on the perturbation model with the two types of separation shocks are depicted in the lower panels (2a,2b)

remarkably close to empirical data, it perform less well in replicating the large autocorrelation of the unemployment rate, the hiring and separation rate (See Shimer, (2005), Mortensen and Pissarides, (1994), Hall, (2005), Mortensen and Nagypal, (2007), and Hagedorn and Manovskii, (2008) for detailed literature about the unemployment-vacancy volatility puzzle).

5.2.2 Comparison to MASON and Netlogo

Rule based modeling frameworks are certainly not the only agent based frameworks that can be used to describe socio-economic systems. Because of their heterogeneity, it is generally difficult to compare agent based systems that are often tailored to different needs so that the model used for benchmarking strongly influences the outcome of the comparison. By using a set of reference models, Railsback, Lytinen, and Jackson, (2006) compared the performance of commonly used agent based frameworks and implications for modelers. They find that Netlogo (Wilensky, 1999) is well suite for small and simple models, prototyping and inexperienced users while MASON (Luke, Cioffi-Revilla, and Panait, 2005) is the fastest of the compared tools and especially suited for models with many agents but requires considerable programming efforts. The template models used in Railsback, Lytinen, and Jackson, (2006) are not applicable to nfsim because they require spatial simulation environments. Here, we describe the implementation of the job-chain model described above in Netlogo and MASON and the comparison of the simulation speed with increasing numbers of agents.

The implementation in Netlogo uses undirected links to generate the job chains and employment interactions but apart from that is basic Netlogo modeling. Although the implementation seems to be straightforward, the simulation engine that iterates over all agents at each timestep to determine events differs fundamentally from the approach used in nfsim where the next rule is sampled from the set of all possible rules and their associated probabilities (Sneddon, Faeder, and Emonet, 2011).

The implementation in MASON that we achieved uses code split over 4 files (when omitting GUI) resulting in about 240 lines of java code. Here, the same problem as with Netlogo occurred: Although agents are supposedly introduced into the scheduler at random positions unless an ordering parameter is specified, it turned out that unless an ordering (job agents before person agents) simulation results do not scale with initial conditions. A possible explanation is that if sufficient person agents are scheduled for execution before empty jobs at the end of chains (the only ones that can be deleted), these deletions can not occur because these jobs will be occupied by persons which eventually leads to an explosion of job chains.

All 3 Models were run on identical CPUs (Intel Xeon, 2.8 GHz, 16 GB RAM). To compare the performance for large models, original initial conditions (1 company, 100 Persons) were multiplied with increasing powers of two from 1 to 16384. The simulation times for the different initial conditions are given in Figure 5.4. Netlogo performed notably worse than MASON and nfsim, aborting due to lack of memory with more than 1600 agents. In our experiments, MASON is consistently twice as fast as nfsim until both simulators abort for lack of memory.

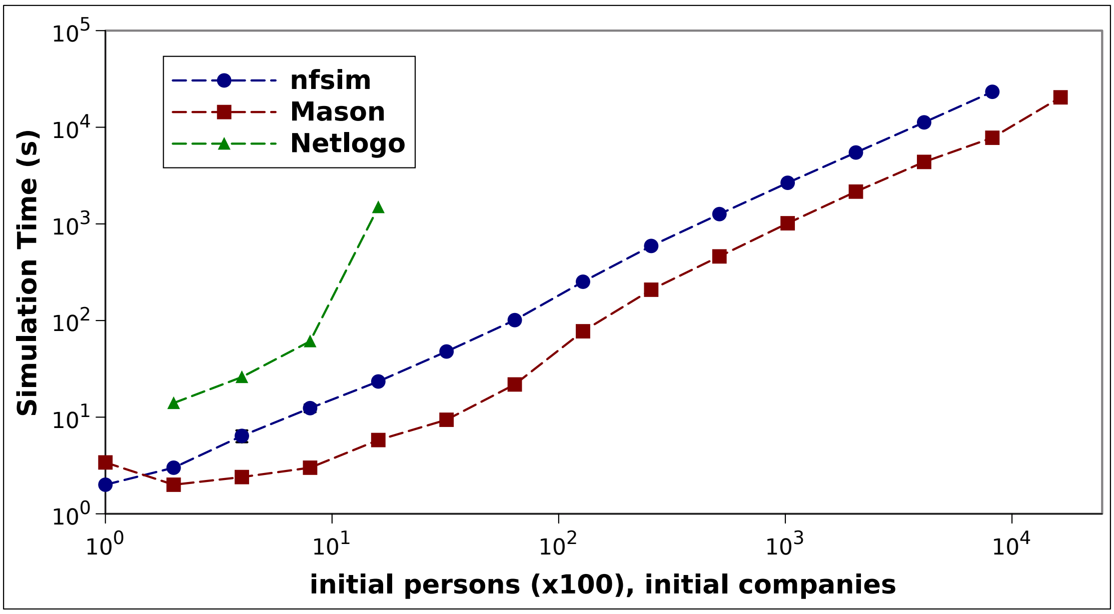


FIGURE 5.4: Simulation duration for simulating the example model for 10000 timesteps in nfsim, MASON, and Netlogo with different initial conditions. For nfsim and MASON, the mean simulation time of 5 stochastic simulations is plotted.

Although we tuned all three model implementations to reproduce similar job, employed, and unemployed numbers, the results do not indicate that MASON is faster than nfsim for the exact same simulation task. Nfsim reports that, for the 6400-person simulation, it executed around 33 million rules. In the same simulation, MASON iterated over all agents (number of persons and companies fixed, number of jobs variable) 10000 times, resulting in about 122 million agent calls. But considering that no more than 0.75 of person agents and only the last jobs in a chain actually execute rules, this results in no more than 18 million rule executions. Although the exact comparison of the two simulation engines is difficult, both scale similarly well with an increase in model size.

5.3 Discussion and Outlook

Rule based modeling is strikingly different from 'traditional' socio-economic agent based frameworks like RePast or MASON. The most eye-catching difference is certainly that neither BioNetGen nor κ consider space. For many applications, though, it is sufficient that agents exist in a well stirred container. In the following, we will summarize and discuss the advantages and disadvantages of RBM with respect to the description of socio-economic systems.

RBM has been successfully applied to biological systems (Bachman and Sorger, 2011). The greatest disadvantage in biology is that the increased level of detail requires additional parameters to be measured or inferred from data, which is often impossible. This is not a problem in socio-economic systems, because a greater amount of detailed empirical data is usually available. Furthermore, exploitation of the advantages of RBM, for example in labor market modeling, does not necessarily require an increase in mechanistic detail compared to existing ABM studies, where sometimes the bargaining process between unemployed and companies is modeled very fine grained (Fagiolo, Dosi, and Gabriele, 2004; Richiardi, 2006).

Here, we implemented a very simple labor market model in nfsim that reproduces empirical data and compared its performance to the established agent based systems Netlogo and Mason. We find that the simulation time of nfsim is comparable to that of MASON for increasing model sizes while both MASON and nfsim outcompete Netlogo by far. It is already difficult to compare relatively similar ABM frameworks correctly (Railsback, Lytinen, and Jackson, 2006). Due to the difference in simulation algorithms, a detailed comparison between MASON and nfsim would need to be based on actual events, which is difficult to realize in MASON without producing additional overhead.

RBM has, at least compared to the frameworks tested in Section 5.2, a very compact syntax: about 50 lines of code are sufficient whereas MASON requires about 240 lines of code. This means that RBM models are highly reusable and are much simpler to extend than current frameworks. Modularity and simple extensibility of submodels would be a great advantage to large-scale modeling approaches like the EURACE project (Holcombe et al., 2013).

The algorithms applied in RBM also differ fundamentally from the way most traditional ABM frameworks simulate time: In nfsim, for example, the next rule execution is sampled from a list of most probable executions instead of traversing all agents and executing the necessary actions. This has the advantage that the order in which the agents are stored or traversed in whatever container is irrelevant. In our opinion, this is an advantage because it prevents modeling errors as described in Section 5.2 and leads to more realistic dynamics. On the other hand, agents, in the current RBM frameworks, have no access to the model time and hence deterministic events, e.g. fixed waiting times, are impossible.

Additionally, mathematical analysis of RBM have already provided methods for constructing deterministic models from stochastic RBMs (Feret et al., 2009; Camporesi, Feret, and Hayman, 2013; Petrov and Koeppl, 2013), which improves the ability to analyze models. Due to the relative novelty of RBM, we expect that the mathematical analysis of rule based models will provide both additional algorithms for the analysis of rule based models (Danos et al., 2012) as well as extensions of rule based models that efficiently deal with the requirements of specific applications.

But these advantages naturally come at a price. The comparably rigid structure of agents and rules leads to shortcomings that affect socio-economic modeling considerably stronger than biological modeling. Some of these are technical issues, namely that sites on agents need to have unique names and no sites can be added to agents. In the case that an agent of one type can bind multiple agents of another type (e.g. jobs on a company), this means that an individual rule for each site would be necessary. In some cases, this can be circumvented by creating agent chains, as exemplified in the model above. Another limitation of current RBM frameworks is the representation of site states by strings rather than integers or floating point numbers and the resulting lack of comparison operators. Simple comparisons, e.g. of reservation wages and job offers, are currently difficult to implement. One possibility is to join ranges of reservation wages and offered wages to groups and compare these in a function.

Although nfsim can handle functions that determine rule execution probabilities, these functions are obfuscated because a sites' state is always a string, so functions usually contain some counting and second, because nfsim does not allow functions to call other functions, functions tend to get very long. While functions are rarely necessary in biological applications of RBM, they seem indispensable for socio-economic modeling, e.g. for computing overall output, wage and price levels.

A significant difference to 'classical' ABM frameworks is that the rigid limitations of the RBM approach require a different way of modeling: Agents and the thus encoded systems are more abstract and limited, so that it is impossible to create full blown computational worlds. Although this is a drawback in certain situations, we are convinced that - in most modeling situations - the premise of a full blown computational world can obstruct more worthwhile endeavors that rely on explicit limitations. The complete freedom of repast and MASON can be an advantage, but it also increases overhead, errors, and learning curve.

The drawbacks are only partly due to the nature of the formalism but also reflect the current state of implementations and their applications. If RBM should come of age in modeling socio-economic systems, one can expect that most of these shortcomings will be resolved.

We hope we have provided a sound example to encourage the reader to peek into RBM formalisms and try to exploit their peculiarities in socio-economic modeling. In our opinion, RBM is an optimal tool for labor market modeling and extensions of the example model could include

- aggregate variables such as dynamically computed company output and profits, prices computed from global wages and company output,
- vocational training tailored to persons' individual traits,

- and computation of simulated employment histories.

The probably greatest advantage of RBM compared to classical ABM frameworks is its compact and unambiguous syntax which enables efficient sharing, extension, and combination of models of different origin: the model we present here can be extended and modified without having to understand java code distributed over different files and written in the developers personal coding style.

Appendix A

A.1 Tables

TABLE A.1: Entry to part-time and full-time self-employment, sample A

	I		II		III	
	part-time	full-time	part-time	full-time	part-time	full-time
age	0.00000	0.00089***	0.00001	0.00091***	0.00001	0.00092***
	(0.13)	(5.27)	(0.50)	(5.44)	(0.49)	(5.49)
age_sq	0.00000	-0.00001***	-0.00000	-0.00001***	-0.00000	-0.00001***
	(0.09)	(-5.37)	(-0.24)	(-5.54)	(-0.23)	(-5.58)
female	0.00011	-0.00209***	0.00010	-0.00207***	0.00010	-0.00206***
	(1.16)	(-4.54)	(1.12)	(-4.55)	(1.12)	(-4.54)
german	0.00006	-0.00116	0.00006	-0.00121	0.00006	-0.00122
	(0.75)	(-0.91)	(0.74)	(-0.95)	(0.75)	(-0.96)
migration	-0.00002	-0.00055	-0.00002	-0.00054	-0.00002	-0.00055
	(-0.39)	(-0.85)	(-0.36)	(-0.84)	(-0.35)	(-0.86)
married	-0.00001	0.00034	-0.00000	0.00035	-0.00000	0.00036
	(-0.19)	(0.68)	(-0.06)	(0.70)	(-0.07)	(0.71)
divorced	-0.00000	-0.00046	-0.00001	-0.00047	-0.00001	-0.00046
	(-0.02)	(-0.62)	(-0.14)	(-0.64)	(-0.14)	(-0.62)
childrenHH_u16	0.00000	-0.00036	0.00000	-0.00039	0.00000	-0.00040
	(0.03)	(-0.81)	(0.03)	(-0.89)	(0.03)	(-0.91)
disabled	0.00010	-0.00182***	0.00008	-0.00180***	0.00008	-0.00178**
	(0.65)	(-2.63)	(0.60)	(-2.61)	(0.60)	(-2.57)
highschool	0.00019	0.00069	0.00014	0.00057	0.00014	0.00056
	(1.07)	(1.19)	(0.98)	(1.01)	(0.99)	(0.99)
apprenticeship	-0.00016	0.00032	-0.00013	0.00038	-0.00013	0.00038
	(-1.15)	(0.59)	(-1.08)	(0.69)	(-1.08)	(0.71)
highertechncol	-0.00009	0.00056	-0.00007	0.00059	-0.00007	0.00060
	(-1.09)	(0.91)	(-1.03)	(0.97)	(-1.03)	(0.98)
university	0.00021	-0.00010	0.00021	-0.00012	0.00021	-0.00012
	(1.11)	(-0.16)	(1.07)	(-0.18)	(1.07)	(-0.18)
parents	0.00023	0.00107	0.00021	0.00105	0.00021	0.00105
	(1.04)	(1.32)	(1.00)	(1.31)	(1.00)	(1.31)
exp_uemp	0.00000	-0.00019	-0.00000	-0.00020	-0.00000	-0.00020
	(0.16)	(-1.38)	(-0.01)	(-1.47)	(-0.02)	(-1.46)
exp_empl_10	0.00001	0.00051	0.00000	0.00052	0.00000	0.00050
	(0.22)	(1.03)	(0.08)	(1.07)	(0.09)	(1.02)
risk	-0.00001	-0.00073**	-0.00001	-0.00072**	-0.00001	-0.00087***
	(-0.29)	(-2.44)	(-0.29)	(-2.43)	(-0.18)	(-2.84)

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Table A.1 – *Continued from previous page*

	I		II		III	
	part-time	full-time	part-time	full-time	part-time	full-time
risk_sq	0.00000	0.00014***	0.00000	0.00014***	0.00000	0.00015***
	(0.95)	(4.95)	(0.91)	(4.90)	(0.84)	(5.00)
tenure	-0.00015	-0.00168***	-0.00015	-0.00165***	-0.00015	-0.00165***
	(-1.56)	(-5.92)	(-1.46)	(-5.84)	(-1.46)	(-5.86)
tenure_sq	0.00002**	0.00009***	0.00002*	0.00009***	0.00002*	0.00009***
	(2.01)	(2.77)	(1.84)	(2.72)	(1.85)	(2.72)
tenure_cu	-0.00000***	-0.00000	-0.00000**	-0.00000	-0.00000**	-0.00000
	(-2.60)	(-1.57)	(-2.31)	(-1.54)	(-2.32)	(-1.53)
incJob1_1000	-0.00002	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001
	(-1.19)	(-1.05)	(-1.12)	(-0.89)	(-1.12)	(-0.88)
incCap_1000	0.00000	0.00002***	0.00000	0.00002***	0.00000	0.00002***
	(0.89)	(4.03)	(0.87)	(4.02)	(0.87)	(4.03)
manager	0.00020	0.00539***	0.00016	0.00535***	0.00015	0.00534***
	(1.00)	(5.68)	(0.93)	(5.68)	(0.93)	(5.69)
Second			0.00044	0.00222***	0.00054	-0.00269**
			(1.16)	(2.85)	(0.92)	(-2.30)
Second×risk					-0.00001	0.00185*
					(-0.17)	(1.94)
Second×risk_sq					0.00000	-0.00013
					(0.05)	(-1.51)
N	88189	88189	88189	88189	88189	88189
mean outcome	0.0024	0.0059	0.0024	0.0059	0.0024	0.0059
Log-Lik		-4170.337		-4145.19		-4142.32

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.2: Robustness: Entry to part-time and full-time self-employment, sample A

	Robust 1		Robust 2		Robust 3	
	part-time	full-time	part-time	full-time	part-time	full-time
female	0.00009	-0.00192***	0.00010	-0.00203***	0.00009	-0.00206***
	(1.07)	(-4.55)	(1.12)	(-4.49)	(0.95)	(-4.65)
parents	0.00028	0.00081	0.00021	0.00111	0.00015	0.00097
	(1.04)	(1.14)	(1.00)	(1.37)	(0.85)	(1.28)
risk_will	-0.00000	-0.00058**	-0.00001	-0.00071**	-0.00002	-0.00056**
	(-0.15)	(-2.14)	(-0.29)	(-2.39)	(-0.60)	(-1.96)
risk_will_sq	0.00000	0.00012***	0.00000	0.00014***	0.00000	0.00012***
	(0.76)	(4.45)	(0.91)	(4.84)	(0.86)	(4.48)
incJob1_1000	-0.00001	0.00000	-0.00001	-0.00001	-0.00001	-0.00001
	(-1.12)	(0.02)	(-1.12)	(-0.69)	(-0.93)	(-1.14)
incCap_1000	0.00000	0.00001***	0.00000	0.00002***	0.00000	0.00002***
	(0.91)	(3.72)	(0.87)	(4.02)	(0.70)	(4.04)
Second	0.00053	0.00207***	0.00044	0.00214***	0.00037	0.00214***
	(1.18)	(2.77)	(1.17)	(2.78)	(0.98)	(2.90)
manager	0.00003	0.00224***	0.00016	0.00525***	0.00013	0.00571***

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Table A.2 – *Continued from previous page*

	Robust 1		Robust 2		Robust 3	
	part-time	full-time	part-time	full-time	part-time	full-time
	(0.38)	(2.83)	(0.93)	(5.63)	(0.81)	(6.15)
manager×smallFirm	0.00023	0.00387***				
	(1.01)	(5.15)				
smallFirm	0.00009	0.00411***				
	(0.89)	(6.06)				
hybIntensity			0.00002	0.00152***		
			(0.58)	(4.48)		
N		77465		88189		92539
mean outcome	0.0024	0.0060	0.0025	0.0059	0.0025	.0059
Log-Lik		-3521.53		-4135.197		-4338.035
χ^2		1197.651		1032.86		1049.844

Marginal effects of a multinomial probit estimation. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Robust 3: The baseline specification is applied to an extented estimation sample including individuals between 58 and 64 years.

TABLE A.3: Entry to hybrid and exclusive self-employment, sample B

	I		II		III	
	hybrid	exclusive	hybrid	exclusive	hybrid	exclusive
age	0.00036**	0.00035***	0.00042***	0.00035***	0.00043***	0.00035***
	(2.19)	(3.76)	(2.73)	(3.84)	(2.75)	(3.84)
age_sq	-0.00000**	-0.00000***	-0.00001***	-0.00000***	-0.00001***	-0.00000***
	(-2.40)	(-3.38)	(-2.90)	(-3.47)	(-2.92)	(-3.47)
female	-0.00083**	-0.00040	-0.00078**	-0.00040*	-0.00078**	-0.00040*
	(-2.02)	(-1.64)	(-1.98)	(-1.65)	(-1.97)	(-1.65)
german	0.00006	-0.00044	0.00001	-0.00046	0.00002	-0.00046
	(0.06)	(-0.64)	(0.01)	(-0.67)	(0.02)	(-0.67)
migration	-0.00012	-0.00046	-0.00010	-0.00046	-0.00010	-0.00046
	(-0.20)	(-1.50)	(-0.17)	(-1.48)	(-0.17)	(-1.48)
married	0.00050	-0.00006	0.00051	-0.00006	0.00052	-0.00006
	(1.02)	(-0.24)	(1.07)	(-0.21)	(1.09)	(-0.21)
divorced	0.00073	-0.00064**	0.00064	-0.00064**	0.00065	-0.00064**
	(0.81)	(-2.13)	(0.74)	(-2.15)	(0.75)	(-2.15)
children	0.00004	-0.00010	-0.00004	-0.00010	-0.00005	-0.00010
	(0.10)	(-0.43)	(-0.10)	(-0.46)	(-0.11)	(-0.46)
disabled	-0.00093	-0.00036	-0.00090	-0.00036	-0.00090	-0.00036
	(-1.12)	(-0.84)	(-1.14)	(-0.85)	(-1.14)	(-0.86)
highschool	0.00190***	-0.00004	0.00150***	-0.00007	0.00150***	-0.00007
	(3.11)	(-0.14)	(2.63)	(-0.26)	(2.63)	(-0.26)
apprenticeship	-0.00025	-0.00051*	-0.00009	-0.00048*	-0.00009	-0.00048*
	(-0.52)	(-1.87)	(-0.18)	(-1.78)	(-0.19)	(-1.78)
highertechncol	-0.00002	-0.00030	0.00009	-0.00028	0.00009	-0.00028
	(-0.04)	(-1.13)	(0.17)	(-1.08)	(0.18)	(-1.08)
university	0.00144**	-0.00050	0.00139**	-0.00049	0.00139**	-0.00049
	(2.09)	(-1.61)	(2.11)	(-1.59)	(2.11)	(-1.59)
parents	0.00159*	0.00068	0.00153*	0.00067	0.00153*	0.00067

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Table A.3 – *Continued from previous page*

	I		II		III	
	hybrid	exclusive	hybrid	exclusive	hybrid	exclusive
	(1.73)	(1.48)	(1.72)	(1.47)	(1.72)	(1.47)
exp_uemp	0.00006	-0.00013	0.00003	-0.00013	0.00003	-0.00013
	(0.51)	(-1.47)	(0.29)	(-1.55)	(0.28)	(-1.55)
exp_empl_10	-0.00018	0.00019	-0.00019	0.00020	-0.00020	0.00020
	(-0.38)	(0.91)	(-0.44)	(0.96)	(-0.45)	(0.96)
risk	-0.00019	-0.00042***	-0.00018	-0.00042***	-0.00034	-0.00042***
	(-0.62)	(-2.84)	(-0.61)	(-2.84)	(-1.02)	(-2.65)
risk_sq	0.00009***	0.00006***	0.00008***	0.00006***	0.00009***	0.00006***
	(2.98)	(4.28)	(2.88)	(4.27)	(3.02)	(4.02)
tenure	-0.00039	-0.00133***	-0.00035	-0.00131***	-0.00035	-0.00131***
	(-1.54)	(-6.39)	(-1.44)	(-6.34)	(-1.44)	(-6.34)
tenure_sq	0.00001	0.00008***	0.00000	0.00008***	0.00000	0.00008***
	(0.20)	(2.89)	(0.13)	(2.86)	(0.13)	(2.86)
tenure_cu	0.00000	-0.00000	0.00000	-0.00000	0.00000	-0.00000
	(0.17)	(-1.64)	(0.23)	(-1.62)	(0.23)	(-1.62)
incJob1_1000	-0.00006***	-0.00001	-0.00005***	-0.00001	-0.00005***	-0.00001
	(-3.30)	(-1.34)	(-2.92)	(-1.23)	(-2.92)	(-1.23)
incCap_1000	0.00001***	0.00001***	0.00001***	0.00001***	0.00001***	0.00001***
	(2.71)	(3.69)	(2.61)	(3.70)	(2.61)	(3.70)
manager	0.00280***	0.00303***	0.00255***	0.00300***	0.00256***	0.00300***
	(3.60)	(4.54)	(3.46)	(4.54)	(3.46)	(4.53)
Second			0.00509***	0.00070*	0.00154	0.00074
			(5.36)	(1.80)	(0.67)	(0.55)
Second×risk					0.00082	0.00001
					(1.17)	(0.01)
Second×risk					-0.00007	-0.00000
					(-1.04)	(-0.03)
N	88189	88189	88189	88189	88189	88189
mean outcome	.0047	.0036	.0047	.0036	.0047	.0036
Log-Lik		-4262.917		-4262.291		-3620.787
χ^2		854.645		861.684		1042.555

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.4: Robustness: Entry to hybrid and exclusive self-employment, sample B

	Robust 1		Robust 2		Robust 3	
	hybrid	exclusive	hybrid	exclusive	hybrid	exclusive
age	0.00046***	0.00023***	0.00041***	0.00035***	0.00034***	0.00032***
	(2.97)	(2.93)	(2.67)	(3.79)	(2.58)	(4.01)
age_sq	-0.00001***	-0.00000***	-0.00001***	-0.00000***	-0.00000***	-0.00000***
	(-3.23)	(-2.83)	(-2.84)	(-3.45)	(-2.76)	(-3.36)
female	-0.00072*	-0.00041**	-0.00075*	-0.00036	-0.00079**	-0.00038
	(-1.88)	(-2.05)	(-1.92)	(-1.52)	(-2.13)	(-1.56)
german	-0.00039	-0.00093	0.00002	-0.00057	-0.00008	-0.00048

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Table A.4 – *Continued from previous page*

	Robust 1		Robust 2		Robust 3	
	hybrid	exclusive	hybrid	exclusive	hybrid	exclusive
	(-0.39)	(-1.19)	(0.02)	(-0.79)	(-0.09)	(-0.71)
migration	-0.00008	-0.00042	-0.00008	-0.00050	-0.00006	-0.00039
	(-0.13)	(-1.61)	(-0.14)	(-1.64)	(-0.10)	(-1.21)
married	0.00026	0.00005	0.00052	-0.00005	0.00053	-0.00005
	(0.55)	(0.23)	(1.10)	(-0.18)	(1.18)	(-0.19)
divorced	0.00039	-0.00026	0.00061	-0.00064**	0.00046	-0.00064**
	(0.48)	(-0.89)	(0.71)	(-2.15)	(0.58)	(-2.17)
children	-0.00003	-0.00016	-0.00005	-0.00014	-0.00002	-0.00014
	(-0.08)	(-0.87)	(-0.11)	(-0.61)	(-0.05)	(-0.64)
disabled	-0.00036	-0.00023	-0.00093	-0.00035	-0.00072	-0.00055
	(-0.41)	(-0.67)	(-1.20)	(-0.82)	(-0.97)	(-1.47)
highschool	0.00180***	-0.00010	0.00151***	-0.00006	0.00155***	-0.00013
	(3.02)	(-0.44)	(2.65)	(-0.20)	(2.80)	(-0.44)
apprenticeship	-0.00004	-0.00036	-0.00009	-0.00047*	0.00004	-0.00050*
	(-0.09)	(-1.58)	(-0.19)	(-1.73)	(0.08)	(-1.87)
highertechncol	0.00020	-0.00025	0.00009	-0.00025	0.00021	-0.00023
	(0.38)	(-1.13)	(0.17)	(-0.96)	(0.42)	(-0.90)
university	0.00151**	-0.00011	0.00134**	-0.00049	0.00120**	-0.00061**
	(2.27)	(-0.39)	(2.04)	(-1.59)	(1.97)	(-2.06)
parents	0.00162*	0.00060	0.00159*	0.00070	0.00138*	0.00060
	(1.84)	(1.56)	(1.77)	(1.51)	(1.68)	(1.39)
pgexp_uemp	0.00001	-0.00010	0.00004	-0.00012	0.00003	-0.00014*
	(0.08)	(-1.27)	(0.38)	(-1.45)	(0.29)	(-1.69)
exp_empl_10	0.00010	0.00032*	-0.00023	0.00021	-0.00023	0.00002
	(0.24)	(1.91)	(-0.54)	(1.01)	(-0.57)	(0.11)
risk_will	-0.00019	-0.00028**	-0.00017	-0.00040***	-0.00018	-0.00037**
	(-0.63)	(-2.35)	(-0.58)	(-2.70)	(-0.62)	(-2.50)
risk_will_sq	0.00008***	0.00004***	0.00008***	0.00006***	0.00008***	0.00006***
	(2.76)	(3.52)	(2.82)	(4.15)	(2.97)	(3.93)
tenure	-0.00042*	-0.00088***	-0.00032	-0.00129***	-0.00035	-0.00132***
	(-1.68)	(-5.35)	(-1.30)	(-6.26)	(-1.53)	(-6.61)
tenure1_sq	0.00001	0.00004**	0.00000	0.00008***	0.00000	0.00008***
	(0.34)	(2.25)	(0.02)	(2.82)	(0.14)	(2.96)
tenure1_cu	0.00000	-0.00000	0.00000	-0.00000	0.00000	-0.00000*
	(0.05)	(-1.07)	(0.32)	(-1.59)	(0.22)	(-1.69)
incJob1_1000	-0.00004***	-0.00000	-0.00005***	-0.00001	-0.00005***	-0.00001
	(-2.86)	(-0.04)	(-2.80)	(-1.08)	(-3.01)	(-1.30)
incCap_1000	0.00001***	0.00001***	0.00001***	0.00001***	0.00001**	0.00001***
	(2.68)	(3.66)	(2.62)	(3.73)	(2.48)	(3.64)
Second	0.00486***	0.00077**	0.00503***	0.00069*	0.00519***	0.00056
	(5.08)	(2.09)	(5.34)	(1.79)	(5.67)	(1.54)
manager	0.00110	0.00086*	0.00249***	0.00295***	0.00257***	0.00336***
	(1.62)	(1.94)	(3.40)	(4.51)	(3.69)	(4.95)
manager×smallFirm	0.00275***	0.00176***				
	(3.61)	(4.37)				
smallFirm	0.00194***	0.00188***				
	(3.56)	(4.73)				
hybIntensity			0.00125***	0.00046***		

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Table A.4 – *Continued from previous page*

	Robust 1		Robust 2		Robust 3	
	hybrid	exclusive	hybrid	exclusive	hybrid	exclusive
			(3.89)	(2.82)		
N	77465	77465	88189	88189	92539	92539
mean outcome	0.0048	0.0036	0.0047	0.0036	0.0047	0.0036
Log-Lik		-3620.787		-4253.570		-4450.064
χ^2		1042.555		878.564		916.589

Marginal effects of a multinomial probit estimation. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Robust 3: The baseline specification is applied to an extented estimation sample including individuals between 58 and 64 years.

TABLE A.5: Entry to part-time hybrid and full-time exclusive self-employment, sample C

	I		II		III	
	pt hybrid	ft exclusive	pt hybrid	ft exclusive	pt hybrid	ft exclusive
age	0.00036**	0.00034***	0.00042***	0.00035***	0.00043***	0.00035***
	(2.19)	(3.72)	(2.73)	(3.80)	(2.75)	(3.80)
age_sq	-0.00000**	-0.00000***	-0.00001***	-0.00000***	-0.00001***	-0.00000***
	(-2.40)	(-3.37)	(-2.90)	(-3.46)	(-2.92)	(-3.46)
female	-0.00083**	-0.00038	-0.00078**	-0.00038	-0.00078**	-0.00038
	(-2.02)	(-1.56)	(-1.98)	(-1.57)	(-1.97)	(-1.57)
german	0.00006	-0.00054	0.00001	-0.00057	0.00001	-0.00056
	(0.06)	(-0.76)	(0.01)	(-0.79)	(0.02)	(-0.79)
migration	-0.00013	-0.00051*	-0.00010	-0.00051*	-0.00011	-0.00051*
	(-0.20)	(-1.67)	(-0.17)	(-1.66)	(-0.18)	(-1.66)
married	0.00051	-0.00005	0.00051	-0.00005	0.00052	-0.00005
	(1.02)	(-0.20)	(1.07)	(-0.17)	(1.09)	(-0.17)
divorced	0.00074	-0.00062**	0.00064	-0.00063**	0.00065	-0.00063**
	(0.81)	(-2.07)	(0.74)	(-2.10)	(0.75)	(-2.10)
children	0.00004	-0.00013	-0.00004	-0.00013	-0.00005	-0.00013
	(0.09)	(-0.56)	(-0.11)	(-0.60)	(-0.12)	(-0.60)
disabled	-0.00093	-0.00035	-0.00090	-0.00035	-0.00090	-0.00035
	(-1.12)	(-0.81)	(-1.14)	(-0.83)	(-1.13)	(-0.83)
highschool	0.00190***	-0.00003	0.00150***	-0.00006	0.00150***	-0.00006
	(3.11)	(-0.09)	(2.63)	(-0.22)	(2.63)	(-0.22)
apprenticeship	-0.00025	-0.00049*	-0.00009	-0.00047*	-0.00009	-0.00047*
	(-0.52)	(-1.80)	(-0.18)	(-1.71)	(-0.19)	(-1.71)
highertechncol	-0.00002	-0.00027	0.00009	-0.00025	0.00009	-0.00025
	(-0.03)	(-1.00)	(0.18)	(-0.95)	(0.18)	(-0.95)
university	0.00144**	-0.00048	0.00139**	-0.00047	0.00139**	-0.00047
	(2.09)	(-1.53)	(2.11)	(-1.51)	(2.11)	(-1.51)
parents	0.00159*	0.000696	0.00153*	0.000683	0.00153*	0.000683
	(1.73)	(1.51)	(1.73)	(1.50)	(1.72)	(1.49)
exp_uemp	0.00006	-0.00012	0.00003	-0.00013	0.00003	-0.00013
	(0.52)	(-1.40)	(0.29)	(-1.47)	(0.29)	(-1.47)
exp_empl_10	-0.00017	0.00021	-0.00019	0.00022	-0.00020	0.00022
	(-0.38)	(1.01)	(-0.43)	(1.05)	(-0.45)	(1.06)

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Table A.5 – *Continued from previous page*

	I		II		III	
	pt hybrid	ft exclusive	pt hybrid	ft exclusive	pt hybrid	ft exclusive
risk	-0.00019	-0.00041***	-0.00018	-0.00040***	-0.00034	-0.00040**
	(-0.62)	(-2.73)	(-0.61)	(-2.72)	(-1.01)	(-2.52)
risk_sq	0.00009***	0.00006***	0.00008***	0.00006***	0.00009***	0.00006***
	(2.98)	(4.19)	(2.87)	(4.18)	(3.01)	(3.91)
tenure	-0.00039	-0.00131***	-0.00035	-0.00130***	-0.00035	-0.00130***
	(-1.54)	(-6.35)	(-1.44)	(-6.30)	(-1.43)	(-6.30)
tenure_sq	0.00001	0.00008***	0.00000	0.00008***	0.00000	0.00008***
	(0.20)	(2.87)	(0.13)	(2.84)	(0.13)	(2.84)
tenure_cu	0.00000	-0.00000	0.00000	-0.00000	0.00000	-0.00000
	(0.18)	(-1.63)	(0.24)	(-1.61)	(0.24)	(-1.61)
incJob1_1000	-0.00006***	-0.00001	-0.00005***	-0.00001	-0.00005***	-0.00001
	(-3.29)	(-1.29)	(-2.92)	(-1.18)	(-2.92)	(-1.18)
incCap_1000	0.00001***	0.00001***	0.00001***	0.00001***	0.00001***	0.00001***
	(2.71)	(3.72)	(2.61)	(3.74)	(2.62)	(3.73)
manager	0.00280***	0.00302***	0.00255***	0.00299***	0.00256***	0.00299***
	(3.60)	(4.54)	(3.46)	(4.53)	(3.46)	(4.52)
Second			0.00509***	0.00072*	0.00155	0.00084
			(5.36)	(1.83)	(0.67)	(0.61)
Second×risk					0.00082	-0.00001
					(1.17)	(-0.04)
Second×risk_sq					-0.00007	0.00000
					(-1.04)	(0.01)
N	88189	88189	88189	88189	88189	88189
mean outcome	0.0047	0.0036	0.0047	0.0036	0.0047	0.0036
Log-Lik		-4294.7		-4262.9		-4262.3
χ^2		774.5		854.6		861.7

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t–statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.6: Part-time transitions, sample A

	I		II		III	
	full-time	exit	full-time	exit	full-time	exit
age	0.05130***	-0.04505***	0.05179***	-0.04471***	0.05230***	-0.04502***
	(4.89)	(-3.91)	(4.88)	(-3.85)	(4.97)	(-3.87)
age_sq	-0.00066***	0.00051***	-0.00067***	0.00051***	-0.00067***	0.00051***
	(-5.31)	(3.60)	(-5.31)	(3.56)	(-5.43)	(3.58)
female	-0.01622	0.03500	-0.01568	0.03550	-0.01773	0.03571
	(-0.71)	(1.05)	(-0.69)	(1.07)	(-0.78)	(1.07)
german	0.08676***	-0.12572	0.08766***	-0.12470	0.08857***	-0.12421
	(3.74)	(-1.51)	(3.83)	(-1.49)	(4.02)	(-1.49)
migration	0.07055	-0.07071	0.07066	-0.07056	0.07538*	-0.06804
	(1.60)	(-1.55)	(1.59)	(-1.55)	(1.68)	(-1.47)
married	-0.02950	-0.03278	-0.02896	-0.03194	-0.02901	-0.03194
	(-1.03)	(-0.88)	(-1.01)	(-0.86)	(-1.01)	(-0.86)

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Table A.6 – *Continued from previous page*

	I		II		III	
	full-time	exit	full-time	exit	full-time	exit
divorced	0.03737	-0.00589	0.03747	-0.00533	0.03635	-0.00804
	(0.91)	(-0.11)	(0.91)	(-0.10)	(0.88)	(-0.15)
children	-0.08727***	-0.01874	-0.08688***	-0.01851	-0.08934***	-0.01976
	(-3.61)	(-0.55)	(-3.59)	(-0.54)	(-3.70)	(-0.57)
disabled	-0.08438***	0.29867***	-0.08452***	0.29786***	-0.08329***	0.30079***
	(-3.85)	(4.31)	(-3.86)	(4.29)	(-3.85)	(4.33)
highschool	-0.02763	-0.06270*	-0.02763	-0.06233*	-0.02903	-0.06178*
	(-1.04)	(-1.77)	(-1.05)	(-1.76)	(-1.11)	(-1.74)
apprenticeship	0.00698	-0.04081	0.00605	-0.04091	0.00703	-0.04056
	(0.27)	(-1.11)	(0.24)	(-1.11)	(0.27)	(-1.10)
highertechncol	0.00910	-0.06277*	0.00839	-0.06254*	0.01065	-0.06173*
	(0.32)	(-1.70)	(0.30)	(-1.70)	(0.37)	(-1.67)
university	0.00053	-0.05272	0.00014	-0.05289	0.00176	-0.05331
	(0.02)	(-1.48)	(0.01)	(-1.48)	(0.07)	(-1.49)
parents	0.00345	-0.01869	0.00328	-0.01926	0.00423	-0.01824
	(0.13)	(-0.47)	(0.12)	(-0.48)	(0.16)	(-0.46)
exp_uemp	0.00059	0.02096***	0.00067	0.02101***	0.00046	0.02092***
	(0.13)	(2.94)	(0.15)	(2.94)	(0.10)	(2.91)
exp_empl_10	0.06831***	-0.06595**	0.06892***	-0.06538**	0.06936***	-0.06446**
	(3.51)	(-2.53)	(3.53)	(-2.50)	(3.56)	(-2.47)
risk	-0.00602	-0.04806**	-0.00641	-0.04846**	-0.00546	-0.05349**
	(-0.36)	(-2.07)	(-0.39)	(-2.09)	(-0.31)	(-2.14)
risk_sq	0.00183	0.00318	0.00186	0.00321	0.00201	0.00385
	(1.24)	(1.43)	(1.25)	(1.44)	(1.30)	(1.58)
tenure	-0.04279	-0.07042**	-0.04233	-0.07002**	-0.04009	-0.07107**
	(-1.58)	(-2.38)	(-1.57)	(-2.37)	(-1.53)	(-2.41)
tenure_sq	0.00617	0.00219	0.00609	0.00214	0.00559	0.00231
	(1.08)	(0.44)	(1.07)	(0.43)	(1.03)	(0.46)
tenure_cu	-0.00028	0.00004	-0.00028	0.00004	-0.00026	0.00003
	(-0.92)	(0.23)	(-0.92)	(0.23)	(-0.90)	(0.19)
incJob1_1000	0.00110	0.00191	0.00106	0.00189	0.00112	0.00179
	(1.10)	(1.09)	(1.07)	(1.07)	(1.13)	(1.03)
incCap_1000	0.00075	-0.00121	0.00075	-0.00122	0.00075	-0.00121
	(1.58)	(-1.45)	(1.57)	(-1.46)	(1.57)	(-1.46)
managerExp	0.04443	0.05361	0.04441	0.05388	0.04026	0.05374
	(1.19)	(1.04)	(1.20)	(1.05)	(1.11)	(1.05)
Second			0.01769	0.01482	0.16122	-0.02997
			(0.61)	(0.35)	(0.63)	(-0.16)
Second×risk					-0.01552	0.03036
					(-0.26)	(0.41)
Second×risk_sq					-0.00059	-0.00405
					(-0.12)	(-0.58)
N	1475	1475	1475	1475	1475	1475
mean outcome	.1426	.2841	.1426	.2841	.1426	.2841
Log-Lik		-1195.777		-1195.43		-1193.14
χ^2		553.137		555.36		560.76

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Table A.6 – *Continued from previous page*

	I		II		III	
	full-time	exit	full-time	exit	full-time	exit

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.7: Hybrid transitions, sample B

	I		II		III	
	excl.	exit	excl.	exit	excl.	exit
age	0.05331***	-0.04500***	0.04636***	-0.04632***	0.04625***	-0.04627***
	(3.66)	(-3.45)	(3.14)	(-3.43)	(3.14)	(-3.42)
age_sq	-0.00057***	0.00055***	-0.00047***	0.00056***	-0.00047***	0.00056***
	(-3.22)	(3.36)	(-2.60)	(3.32)	(-2.60)	(3.33)
female	-0.13409***	0.09339***	-0.13265***	0.09446***	-0.13236***	0.09423***
	(-3.63)	(2.64)	(-3.57)	(2.63)	(-3.56)	(2.62)
german	-0.12417	0.01361	-0.12824	0.01797	-0.12896*	0.01743
	(-1.58)	(0.19)	(-1.64)	(0.24)	(-1.65)	(0.24)
migration	-0.04239	0.00274	-0.04596	0.00188	-0.04686	0.00121
	(-0.66)	(0.05)	(-0.72)	(0.03)	(-0.73)	(0.02)
married	0.07384	-0.07106*	0.07606	-0.06926	0.07750*	-0.07023
	(1.60)	(-1.69)	(1.64)	(-1.62)	(1.67)	(-1.64)
divorced	0.06056	-0.04465	0.05529	-0.04429	0.05592	-0.04464
	(0.92)	(-0.76)	(0.84)	(-0.74)	(0.85)	(-0.75)
children	-0.02995	0.00421	-0.02237	0.00328	-0.02361	0.00421
	(-0.76)	(0.11)	(-0.57)	(0.09)	(-0.60)	(0.11)
disabled	-0.08101	0.05726	-0.08838	0.06221	-0.08800	0.06120
	(-0.76)	(0.62)	(-0.86)	(0.66)	(-0.86)	(0.65)
highschool	-0.06165	0.02839	-0.05253	0.03034	-0.05362	0.03093
	(-1.41)	(0.67)	(-1.20)	(0.70)	(-1.22)	(0.72)
apprenticeship	-0.01830	0.00635	-0.02584	0.00360	-0.02712	0.00403
	(-0.40)	(0.15)	(-0.55)	(0.08)	(-0.58)	(0.09)
highertechncol	-0.08592*	0.04518	-0.08442*	0.04744	-0.08541*	0.04787
	(-1.78)	(0.96)	(-1.73)	(0.99)	(-1.75)	(1.00)
university	0.04481	-0.06301	0.06121	-0.06618	0.06043	-0.06578
	(0.93)	(-1.41)	(1.25)	(-1.46)	(1.24)	(-1.45)
parents	-0.03695	-0.00723	-0.01816	-0.00579	-0.01635	-0.00597
	(-0.67)	(-0.15)	(-0.33)	(-0.12)	(-0.29)	(-0.12)
exp_uemp	-0.02572**	0.02871***	-0.02817***	0.02962***	-0.02805***	0.02966***
	(-2.52)	(3.31)	(-2.82)	(3.33)	(-2.79)	(3.33)
exp_empl_10	-0.00699	-0.05385	-0.00967	-0.05431	-0.00916	-0.05454
	(-0.19)	(-1.60)	(-0.26)	(-1.58)	(-0.24)	(-1.59)
risk	0.07191***	-0.06980***	0.08099***	-0.07051***	0.06629*	-0.06591**
	(2.64)	(-2.74)	(2.96)	(-2.73)	(1.90)	(-2.01)
risk_sq	-0.00471*	0.00579**	-0.00536**	0.00583**	-0.00402	0.00533*
	(-1.86)	(2.47)	(-2.10)	(2.45)	(-1.21)	(1.74)
tenure	0.32225	-0.46231	0.38061	-0.47414	0.38391	-0.48033
	(1.16)	(-1.40)	(1.33)	(-1.41)	(1.34)	(-1.43)

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Table A.7 – *Continued from previous page*

	I		II		III	
	excl.	exit	excl.	exit	excl.	exit
tenure_sq	-0.16929	0.18316	-0.18015	0.19006	-0.18160	0.19271
	(-1.55)	(1.40)	(-1.61)	(1.42)	(-1.61)	(1.44)
tenure_cu	0.01918*	-0.02076	0.02009*	-0.02173	0.02025*	-0.02202
	(1.67)	(-1.45)	(1.69)	(-1.48)	(1.70)	(-1.49)
incJob1_1000	-0.00044	0.00128*	-0.00205**	0.00109	-0.00207**	0.00110
	(-0.46)	(1.66)	(-2.28)	(1.32)	(-2.31)	(1.34)
incCap_1000	-0.00145*	0.00006	-0.00113	0.00009	-0.00112	0.00009
	(-1.83)	(0.06)	(-1.43)	(0.09)	(-1.41)	(0.09)
manager	-0.00685	-0.01410	-0.02131	-0.01327	-0.01901	-0.01433
	(-0.13)	(-0.31)	(-0.40)	(-0.29)	(-0.36)	(-0.31)
Second			-0.18173***	-0.01578	-0.27403*	0.01608
			(-4.70)	(-0.44)	(-1.81)	(0.12)
Second×risk					0.04144	-0.01855
					(0.66)	(-0.35)
Second×risk_sq					-0.00376	0.00185
					(-0.64)	(0.37)
N	994	994	994	994	994	994
mean outcome	.5113	.3014	.5113	.3014	.5113	.3014
Log-Lik		-904.911		-882.044		-881.764
χ^2		234.486		262.843		264.933

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.8: Full-time transitions, sample A

	I		II		III	
	part-time	exit	part-time	exit	part-time	exit
age	0.00173	-0.01290***	0.00178	-0.01294***	0.00179	-0.01295***
	(1.30)	(-2.64)	(1.33)	(-2.64)	(1.34)	(-2.65)
age_sq	-0.00001	0.00016***	-0.00001	0.00017***	-0.00001	0.00017***
	(-0.42)	(2.93)	(-0.46)	(2.94)	(-0.47)	(2.94)
female	0.02511***	-0.01402	0.02487***	-0.01390	0.02494***	-0.01414
	(5.40)	(-1.41)	(5.36)	(-1.39)	(5.39)	(-1.41)
german	0.00335	-0.03965	0.00331	-0.03959	0.00287	-0.03891
	(0.52)	(-1.37)	(0.52)	(-1.37)	(0.44)	(-1.35)
migration	-0.00408	0.00382	-0.00420	0.00389	-0.00441	0.00462
	(-1.01)	(0.23)	(-1.06)	(0.24)	(-1.13)	(0.28)
married	-0.00726*	0.00775	-0.00720*	0.00771	-0.00721*	0.00764
	(-1.92)	(0.65)	(-1.91)	(0.65)	(-1.91)	(0.65)
divorced	-0.00359	0.02136	-0.00350	0.02130	-0.00351	0.02154
	(-1.02)	(1.20)	(-0.99)	(1.20)	(-0.99)	(1.21)
children	0.00152	0.00120	0.00142	0.00126	0.00155	0.00112
	(0.52)	(0.12)	(0.49)	(0.12)	(0.54)	(0.11)
disabled	0.01235	0.07624**	0.01256	0.07604**	0.01248	0.07661**
	(1.18)	(2.43)	(1.19)	(2.43)	(1.19)	(2.44)

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Table A.8 – *Continued from previous page*

	I		II		III	
	part-time	exit	part-time	exit	part-time	exit
highschool	-0.00565*	-0.02262*	-0.00571*	-0.02259*	-0.00585*	-0.02228*
	(-1.72)	(-1.91)	(-1.74)	(-1.90)	(-1.78)	(-1.88)
apprenticeship	0.00097	-0.01292	0.00087	-0.01286	0.00083	-0.01269
	(0.26)	(-1.06)	(0.23)	(-1.06)	(0.22)	(-1.04)
highertechncol	0.00601	-0.01530	0.00576	-0.01515	0.00573	-0.01503
	(1.34)	(-1.24)	(1.29)	(-1.23)	(1.29)	(-1.22)
university	0.00517	-0.04345***	0.00507	-0.04338***	0.00509	-0.04325***
	(1.28)	(-3.56)	(1.26)	(-3.55)	(1.27)	(-3.54)
parents	-0.00432	-0.00927	-0.00433	-0.00923	-0.00418	-0.00956
	(-1.37)	(-0.77)	(-1.38)	(-0.77)	(-1.33)	(-0.79)
exp_uemp	0.00113	0.00327	0.00111	0.00329	0.00111	0.00318
	(1.51)	(1.03)	(1.47)	(1.04)	(1.47)	(1.00)
exp_empl_10	-0.00826***	-0.02922***	-0.00822***	-0.02926***	-0.00821***	-0.02934***
	(-3.33)	(-2.66)	(-3.31)	(-2.67)	(-3.32)	(-2.67)
risk	0.00265	-0.01311*	0.00267	-0.01313*	0.00228	-0.01115
	(1.15)	(-1.88)	(1.15)	(-1.88)	(0.97)	(-1.55)
risk_sq	-0.00022	0.00135**	-0.00022	0.00135**	-0.00020	0.00117*
	(-1.05)	(2.09)	(-1.06)	(2.09)	(-0.93)	(1.76)
tenure	-0.01159***	-0.04780***	-0.01151***	-0.04786***	-0.01150***	-0.04790***
	(-6.64)	(-7.41)	(-6.64)	(-7.40)	(-6.62)	(-7.42)
tenure_sq	0.00094***	0.00385***	0.00093***	0.00385***	0.00093***	0.00386***
	(4.43)	(4.74)	(4.43)	(4.74)	(4.41)	(4.76)
tenure_cu	-0.00002***	-0.00010***	-0.00002***	-0.00010***	-0.00002***	-0.00010***
	(-3.14)	(-3.72)	(-3.14)	(-3.72)	(-3.12)	(-3.75)
incJob1_1000	-0.00037	0.00035	-0.00037	0.00035	-0.00038	0.00036
	(-1.50)	(0.75)	(-1.49)	(0.75)	(-1.51)	(0.76)
incCap_1000	-0.00005	0.00002	-0.00005	0.00002	-0.00005	0.00002
	(-1.06)	(1.06)	(-1.05)	(1.05)	(-1.04)	(1.04)
manager	0.00023	0.01704	0.00016	0.01706	0.00020	0.01675
	(0.06)	(1.30)	(0.04)	(1.30)	(0.06)	(1.28)
Second			0.00385	-0.00278	-0.01011	0.09482
			(0.71)	(-0.15)	(-1.06)	(0.95)
Second×risk					0.00518	-0.03852
					(0.56)	(-1.20)
Second×risk_sq					-0.00028	0.00354
					(-0.35)	(1.14)
N	7450	7450	7450	7450	7450	7450
mean outcome	.0249	.1610	.0249	.1610	.0249	.1610
Log-Lik		-3768.486		-3768.192		-3766.871
χ^2		671.105		671.827		677.895

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.9: Robustness: Full-time exclusive transitions, sample C

	I	
	hybrid	exit
age	-0.00242	-0.02200***
	(-1.33)	(-4.55)
age_sq	0.00003	0.00027***
	(1.45)	(4.96)
female	0.00912**	-0.00291
	(2.05)	(-0.29)
german	0.00196	-0.05676*
	(0.24)	(-1.82)
migration	0.00137	-0.00451
	(0.22)	(-0.28)
married	-0.00549	0.01184
	(-1.18)	(0.99)
divorced	-0.00353	0.02357
	(-0.66)	(1.25)
children	0.00382	0.00302
	(0.97)	(0.29)
disabled	0.00733	0.13190***
	(0.70)	(4.09)
highschool	-0.00102	-0.03656***
	(-0.23)	(-3.09)
apprenticeship	-0.00010	-0.02985**
	(-0.02)	(-2.44)
highertechncol	0.00509	-0.03173**
	(0.87)	(-2.53)
university	0.01198**	-0.04991***
	(2.26)	(-4.03)
parents	-0.00295	-0.00259
	(-0.65)	(-0.20)
exp_uemp	-0.00107	0.00258
	(-0.77)	(0.84)
exp_empl_10	-0.00065	-0.04682***
	(-0.17)	(-4.95)
risk	-0.00111	-0.01112
	(-0.42)	(-1.54)
risk_sq	0.00010	0.00117*
	(0.41)	(1.73)
tenure	-0.00926***	-0.05273***
	(-4.39)	(-8.03)
tenure_sq	0.00076***	0.00414***
	(2.89)	(4.90)
tenure_cu	-0.00002**	-0.00010***
	(-2.11)	(-3.65)
incJob1_1000	—	—
incCap_1000	-0.00000	0.00001
	(-0.18)	(0.48)
manager	-0.00309	0.01469

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Table A.9 – *Continued from previous page*

	I	
	hybrid	exit
	(-0.69)	(1.07)
N	7943	7943
mean outcome	.0231	.1782
Log-Lik		-4191.535
χ^2		665.798

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. By definition of full-time self-employment in sample B, full-time entrepreneurs do not have income from a primar wage job, so *incJob1_1000* is omitted from the model specification. t statistics in parentheses $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.10: Robustness: Hybrid transitions

	I		II		III	
	ft-excl.	exit	ft-excl.	exit	ft-excl.	exit
age	0.05343***	-0.04109***	0.04662***	-0.04294***	0.04680***	-0.04342***
	(3.58)	(-3.43)	(3.07)	(-3.44)	(3.08)	(-3.47)
age_sq	-0.00058***	0.00049***	-0.00048**	0.00051***	-0.00048**	0.00052***
	(-3.13)	(3.25)	(-2.55)	(3.24)	(-2.55)	(3.25)
female	-0.15383***	0.11719***	-0.14987***	0.12090***	-0.15013***	0.12104***
	(-4.07)	(3.50)	(-3.98)	(3.51)	(-3.99)	(3.50)
german	-0.12741	0.00702	-0.12849	0.00898	-0.13177*	0.01164
	(-1.59)	(0.10)	(-1.63)	(0.12)	(-1.67)	(0.16)
migration	-0.03148	-0.02679	-0.02989	-0.02910	-0.03341	-0.02698
	(-0.44)	(-0.54)	(-0.44)	(-0.57)	(-0.49)	(-0.52)
married	0.07353	-0.07124*	0.07628	-0.07155*	0.07603	-0.06984*
	(1.56)	(-1.75)	(1.63)	(-1.71)	(1.62)	(-1.67)
divorced	0.05818	-0.03028	0.05083	-0.03089	0.05044	-0.03035
	(0.88)	(-0.55)	(0.76)	(-0.55)	(0.76)	(-0.54)
children	-0.03071	0.00354	-0.02167	0.00349	-0.02049	0.00150
	(-0.76)	(0.10)	(-0.54)	(0.10)	(-0.51)	(0.04)
disabled	-0.13887	0.13058	-0.14747	0.13140	-0.14999	0.13500
	(-1.23)	(1.30)	(-1.37)	(1.27)	(-1.38)	(1.27)
highschool	-0.07842*	0.04038	-0.06560	0.04402	-0.06783	0.04632
	(-1.74)	(1.05)	(-1.46)	(1.11)	(-1.50)	(1.16)
apprenticeship	-0.00574	-0.00484	-0.00899	-0.00782	-0.01058	-0.00828
	(-0.12)	(-0.12)	(-0.18)	(-0.19)	(-0.22)	(-0.20)
highertechncol	-0.08455	0.03779	-0.08171	0.03836	-0.08313	0.03902
	(-1.64)	(0.85)	(-1.59)	(0.85)	(-1.61)	(0.86)
university	0.05185	-0.05737	0.07079	-0.06079	0.07030	-0.06135
	(1.05)	(-1.38)	(1.41)	(-1.41)	(1.39)	(-1.42)
parents	0.01943	-0.08883**	0.04527	-0.08959**	0.04762	-0.08931**
	(0.35)	(-2.39)	(0.82)	(-2.33)	(0.86)	(-2.30)
exp_uemp	-0.02198**	0.02572***	-0.02527**	0.02634***	-0.02532**	0.02656***
	(-2.00)	(3.35)	(-2.42)	(3.35)	(-2.41)	(3.36)
exp_empl_10	-0.00224	-0.05499*	-0.00186	-0.05399	-0.00244	-0.05264
	(-0.06)	(-1.70)	(-0.05)	(-1.62)	(-0.06)	(-1.57)

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Table A.10 – *Continued from previous page*

	I		II		III	
	ft-excl.	exit	ft-excl.	exit	ft-excl.	exit
risk	0.07281**	-0.06471***	0.08734***	-0.06460***	0.07765**	-0.07415**
	(2.52)	(-2.73)	(3.02)	(-2.68)	(2.00)	(-2.51)
risk_sq	-0.00491*	0.00556**	-0.00612**	0.00553**	-0.00546	0.00675**
	(-1.83)	(2.53)	(-2.27)	(2.48)	(-1.46)	(2.40)
incJob1_1000	-0.00058	0.00171***	-0.00250***	0.00150**	-0.00251***	0.00147**
	(-0.58)	(2.64)	(-2.83)	(2.14)	(-2.84)	(2.14)
incCap_1000	-0.00162**	0.00037	-0.00137*	0.00039	-0.00135*	0.00039
	(-2.02)	(0.39)	(-1.70)	(0.41)	(-1.68)	(0.41)
manager	0.00571	-0.03254	-0.01079	-0.03000	-0.00932	-0.02951
	(0.11)	(-0.77)	(-0.20)	(-0.69)	(-0.17)	(-0.67)
Second			-0.20137***	-0.01208	-0.27043	-0.02817
			(-4.97)	(-0.36)	(-1.59)	(-0.23)
Second×risk					0.01512	0.02028
					(0.22)	(0.38)
Second×risk_sq					-0.00056	-0.00280
					(-0.09)	(-0.57)
N	928	928	928	928	928	928
mean outcome	0.5477	0.2517	0.5477	0.2517	0.5477	0.2517
Log-Lik		-815.592		-792.662		-791.865
χ^2		258.095		283.141		291.088

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.11: Comparison logit model: Entry to self-employment

	I	II	III	Robust 1	Robust 2	Robust 3
age	0.00073***	0.00078***	0.00078***	0.00067***	0.00077***	0.00066***
	(4.04)	(4.41)	(4.42)	(4.01)	(4.38)	(4.41)
age_sq	-0.00001***	-0.00001***	-0.00001***	-0.00001***	-0.00001***	-0.00001***
	(-3.83)	(-4.18)	(-4.20)	(-4.03)	(-4.14)	(-3.95)
female	-0.00112**	-0.00106**	-0.00105**	-0.00110**	-0.00100**	-0.00105**
	(-2.28)	(-2.20)	(-2.19)	(-2.52)	(-2.08)	(-2.27)
german	-0.00050	-0.00063	-0.00061	-0.00157	-0.00063	-0.00067
	(-0.40)	(-0.51)	(-0.50)	(-1.17)	(-0.51)	(-0.57)
migration	-0.00070	-0.00064	-0.00064	-0.00060	-0.00062	-0.00046
	(-1.00)	(-0.94)	(-0.93)	(-0.92)	(-0.91)	(-0.68)
married	0.00027	0.00031	0.00031	0.00025	0.00031	0.00033
	(0.48)	(0.56)	(0.57)	(0.48)	(0.57)	(0.62)
divorced	-0.00054	-0.00058	-0.00057	-0.00020	-0.00063	-0.00070
	(-0.65)	(-0.72)	(-0.70)	(-0.25)	(-0.77)	(-0.91)
children	0.00002	-0.00006	-0.00006	-0.00008	-0.00006	-0.00005
	(0.04)	(-0.12)	(-0.13)	(-0.18)	(-0.13)	(-0.11)
disabled	-0.00118	-0.00117	-0.00117	-0.00059	-0.00117	-0.00136
	(-1.26)	(-1.27)	(-1.28)	(-0.69)	(-1.27)	(-1.64)
highschool	0.00155**	0.00121*	0.00121*	0.00130**	0.00121*	0.00114*

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Table A.11 – *Continued from previous page*

	I	II	III	Robust 1	Robust 2	Robust 3
	(2.27)	(1.87)	(1.86)	(2.12)	(1.86)	(1.80)
apprenticeship	-0.00083	-0.00062	-0.00062	-0.00055	-0.00065	-0.00054
	(-1.42)	(-1.09)	(-1.08)	(-1.06)	(-1.14)	(-0.99)
highertechncol	-0.00025	-0.00014	-0.00014	-0.00020	-0.00015	-0.00002
	(-0.42)	(-0.25)	(-0.24)	(-0.37)	(-0.26)	(-0.04)
university	0.00040	0.00044	0.00045	0.00084	0.00035	0.00010
	(0.51)	(0.58)	(0.59)	(1.19)	(0.47)	(0.15)
parents	0.00193**	0.00186**	0.00184**	0.00192**	0.00190**	0.00165**
	(2.10)	(2.08)	(2.06)	(2.35)	(2.11)	(1.98)
exp_uemp	-0.00014	-0.00015	-0.00015	-0.00017	-0.00015	-0.00017
	(-0.92)	(-1.05)	(-1.07)	(-1.13)	(-1.01)	(-1.23)
exp_empl_10	0.00027	0.00029	0.00029	0.00062	0.00024	-0.00003
	(0.53)	(0.58)	(0.58)	(1.43)	(0.49)	(-0.06)
risk	-0.00069**	-0.00067**	-0.00082**	-0.00057*	-0.00066**	-0.00058*
	(-2.11)	(-2.08)	(-2.34)	(-1.94)	(-2.05)	(-1.89)
risk_sq	0.00015***	0.00015***	0.00016***	0.00012***	0.00015***	0.00014***
	(4.98)	(4.87)	(4.92)	(4.44)	(4.83)	(4.69)
tenure	-0.00231***	-0.00221***	-0.00220***	-0.00186***	-0.00217***	-0.00219***
	(-6.25)	(-6.10)	(-6.10)	(-5.62)	(-6.03)	(-6.42)
tenure_sq	0.00014***	0.00013***	0.00013***	0.00010**	0.00013***	0.00013***
	(2.78)	(2.69)	(2.69)	(2.30)	(2.64)	(2.84)
tenure_cu	-0.00000*	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000*
	(-1.65)	(-1.60)	(-1.60)	(-1.26)	(-1.56)	(-1.72)
incJob1_1000	-0.00006***	-0.00005**	-0.00005**	-0.00002*	-0.00004**	-0.00004**
	(-2.67)	(-2.34)	(-2.34)	(-1.72)	(-2.20)	(-2.47)
incCap_1000	0.00001***	0.00001***	0.00001***	0.00001***	0.00001***	0.00001***
	(4.61)	(4.44)	(4.45)	(4.47)	(4.46)	(4.30)
manager	0.00566***	0.00542***	0.00540***	0.00163**	0.00533***	0.00580***
	(5.61)	(5.51)	(5.51)	(2.04)	(5.46)	(6.02)
Second		0.00481***	0.00224	0.00458***	0.00477***	0.00467***
		(5.25)	(0.84)	(5.17)	(5.23)	(5.38)
Second×risk			0.00081			
			(1.02)			
Second×risk_sq			-0.00008			
			(-1.06)			
manager×smallFirm				0.00452***		
				(5.64)		
smallFirm				0.00433***		
				(6.09)		
hybIntensity					0.00119***	
					(4.09)	
N	88189	88189	88189	77465	88189	92539
mesn outcome	0.0084	0.00834	0.0084	0.0084	0.0084	0.0084
pseudo R^2	0.085	0.091	0.091	0.128	0.093	0.093
Log-Lik	-3896.839	-3871.741	-3871.157	-3280.592	-3863.411	-4039.938
χ^2	747.170	834.919	831.788	1087.158	793.574	861.887

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.12: Comparison logit model: Self-employment survival

	I	II	III	Robust 1	Robust 2	Robust 3
age	-0.01683***	-0.01651***	-0.01654***	-0.01525***	-0.01649***	-0.02013***
	(-6.11)	(-5.95)	(-5.96)	(-5.39)	(-5.95)	(-8.59)
age_sq	0.00021***	0.00020***	0.00020***	0.00018***	0.00020***	0.00025***
	(6.31)	(6.17)	(6.17)	(5.44)	(6.16)	(9.60)
female	0.03355***	0.03302***	0.03313***	0.03146***	0.03291***	0.03286***
	(4.57)	(4.50)	(4.52)	(4.25)	(4.49)	(4.57)
german	-0.04141**	-0.04117*	-0.04118*	-0.04107*	-0.04135*	-0.04346**
	(-1.96)	(-1.95)	(-1.95)	(-1.90)	(-1.96)	(-2.08)
migration	-0.00925	-0.00922	-0.00930	-0.01200	-0.00948	-0.00947
	(-0.90)	(-0.90)	(-0.90)	(-1.15)	(-0.92)	(-0.94)
married	-0.00170	-0.00150	-0.00127	-0.00427	-0.00153	0.00012
	(-0.21)	(-0.18)	(-0.16)	(-0.51)	(-0.19)	(0.01)
divorced	0.01031	0.01042	0.01045	0.01767	0.00985	0.00327
	(0.81)	(0.82)	(0.82)	(1.30)	(0.78)	(0.27)
children	0.01383*	0.01374*	0.01355*	0.01329*	0.01378*	0.01595**
	(1.91)	(1.90)	(1.87)	(1.80)	(1.91)	(2.20)
disabled	0.09958***	0.09956***	0.09949***	0.08978***	0.09914***	0.07796***
	(3.83)	(3.83)	(3.82)	(3.34)	(3.80)	(3.60)
highschool	-0.00522	-0.00536	-0.00543	-0.00700	-0.00534	-0.00595
	(-0.66)	(-0.68)	(-0.69)	(-0.86)	(-0.68)	(-0.78)
apprenticeship	-0.00970	-0.00966	-0.00977	-0.00801	-0.00976	-0.00812
	(-1.15)	(-1.15)	(-1.16)	(-0.94)	(-1.16)	(-0.98)
highertechncol	-0.00934	-0.00958	-0.00958	-0.00890	-0.00985	-0.01068
	(-1.07)	(-1.10)	(-1.10)	(-1.02)	(-1.13)	(-1.26)
university	-0.03169***	-0.03179***	-0.03184***	-0.02731***	-0.03178***	-0.03401***
	(-3.78)	(-3.79)	(-3.80)	(-3.21)	(-3.79)	(-4.17)
parents	-0.02237***	-0.02251***	-0.02248***	-0.02134***	-0.02287***	-0.01482*
	(-2.80)	(-2.81)	(-2.81)	(-2.63)	(-2.87)	(-1.85)
exp_uemp	0.00713***	0.00710***	0.00712***	0.00685***	0.00712***	0.00817***
	(3.95)	(3.94)	(3.94)	(3.59)	(3.95)	(4.60)
exp_empl_10	-0.02272***	-0.02259***	-0.02245***	-0.01958***	-0.02268***	-0.02508***
	(-3.64)	(-3.62)	(-3.60)	(-3.05)	(-3.64)	(-4.51)
risk	-0.01292***	-0.01295***	-0.01412***	-0.01548***	-0.01267***	-0.01088**
	(-2.77)	(-2.77)	(-2.88)	(-3.27)	(-2.72)	(-2.36)
risk_sq	0.00119***	0.00119***	0.00131***	0.00143***	0.00116***	0.00096**
	(2.71)	(2.71)	(2.82)	(3.19)	(2.64)	(2.20)
tenure	-0.04473***	-0.04435***	-0.04440***	-0.04238***	-0.04451***	-0.04858***
	(-8.43)	(-8.34)	(-8.35)	(-7.90)	(-8.38)	(-10.06)
tenure_sq	0.00369***	0.00365***	0.00365***	0.00352***	0.00367***	0.00421***
	(4.87)	(4.83)	(4.83)	(4.68)	(4.87)	(6.36)
tenure_cu	-0.00009***	-0.00009***	-0.00009***	-0.00009***	-0.00009***	-0.00011***
	(-3.50)	(-3.47)	(-3.47)	(-3.40)	(-3.52)	(-4.85)
incJob1_1000	0.00033	0.00033	0.00032	0.00028	0.00033	0.00039
	(1.28)	(1.27)	(1.27)	(1.04)	(1.29)	(1.62)
incCap_1000	0.00003**	0.00003***	0.00003**	0.00002**	0.00003***	0.00003**
	(2.57)	(2.58)	(2.55)	(2.35)	(2.61)	(2.55)

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Table A.12 – *Continued from previous page*

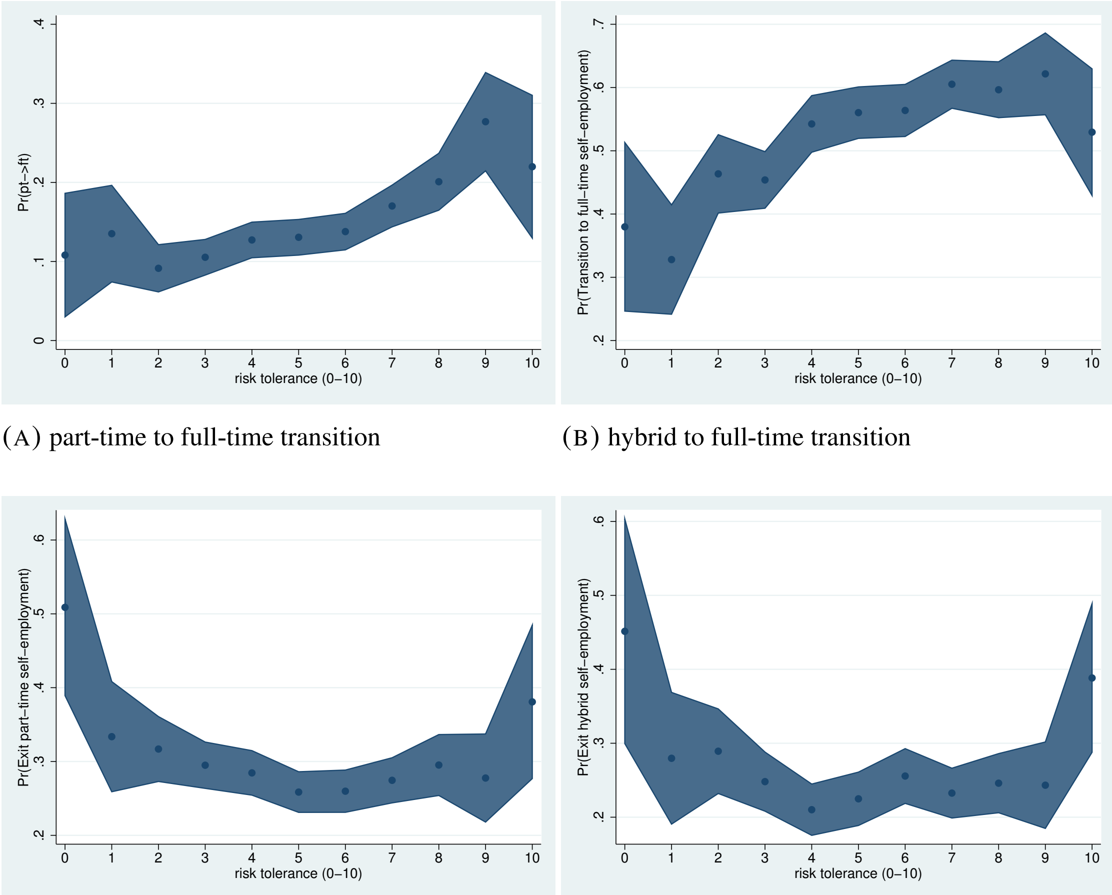
	I	II	III	Robust 1	Robust 2	Robust 3
manager	0.02208**	0.02203**	0.02215**	0.02013	0.02188**	0.02532**
	(2.03)	(2.02)	(2.03)	(1.25)	(2.01)	(2.35)
Second		0.01313	-0.01615	0.01806	0.00788	0.01597
		(1.15)	(-0.42)	(1.50)	(0.70)	(1.40)
Second×risk			0.01567			
			(0.85)			
Second×risk_sq			-0.00159			
			(-0.90)			
manager×smallFirm				0.00676		
				(0.38)		
smallFirm				-0.00480		
				(-0.73)		
hybIntensity					0.00063**	
					(2.14)	
N	9048	9048	9048	8387	9048	9830
mean outcome	0.1207	0.1207	0.1207	0.1207	0.1207	0.1207
pseudo R^2	0.114	0.114	0.114	0.111	0.115	0.117
Log-Lik	-2953.254	-2952.540	-2952.060	-2681.156	-2949.823	-3262.161
χ^2	661.897	665.510	664.334	590.409	765.053	754.324

Marginal effects after multinomial probit estimation, evaluated at the means of the continuous and ordinal scaled explanatory variables and at a discrete change from 0 to 1 for dummy variables. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.13: Variable labels and description

Variable	Description
Second	Dummy if individual holds a secondary job
age	Age of individual
age_sq	Age squared
female	Dummy for female respondents
german	Dummy for German nationality
migration	Dummy for migrational background
married	Dummy for married individuals
divorced	Dummy for divorced individuals
children	Dummy for children younger than 16 years in household
disabled	Dummy for handicapped persons
highschool	Dummy for individuals who finished higher secondary school ((*Fach-)Hochschulreife*)
apprenticeship	Dummy for individuals who finished an apprenticeship (*Lehre*)
highertechncol	Dummy for individuals who finished a higher technical college
university	Dummy for individuals with a university degree
parents	Dummy for individuals whose father/mother was selfemployed when the respondent was 15 years old
exp_uemp	Years of unemployment experience prior to the year of observation
exp_empl_10	Years of employment experience prior to the year of observation, divided by 10
incCap_1000	Real income from interests, dividends and renting out in the year prior to observation (in thousand euros)
incJob1_1000	Earnings from primary job (in thousand euros)
tenure	duration of the current spell, in years
tenure_sq	duration, squared
tenure_cu	duration, cubic
risk	risk propensity (11-point likert scale)
risk_sq	risk propensity, squared
manager	Dummy for individuals who hold (held) a managerial position in their current (previous) job
smallFirm	Dummy for individuals who are (were) employed in a small-sized company
hybIntensity	ratio of income from self-employment to sum of earnings from wage job and self-employment

A.2 Figures



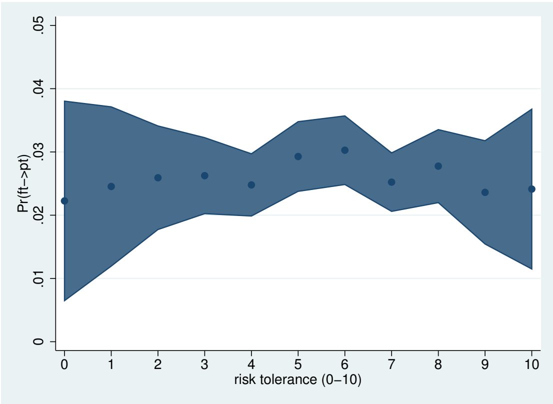
(A) part-time to full-time transition

(B) hybrid to full-time transition

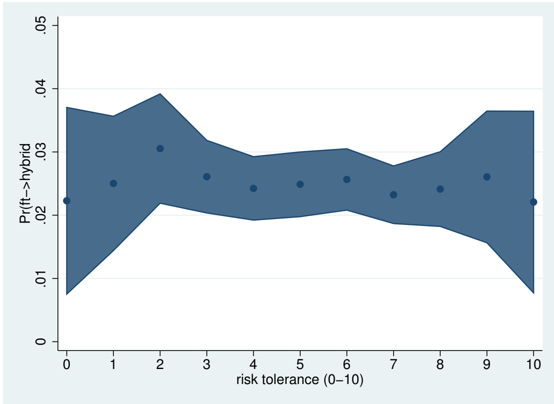
(C) Failure of part-time self-employment

(D) Failure of hybrid self-employment

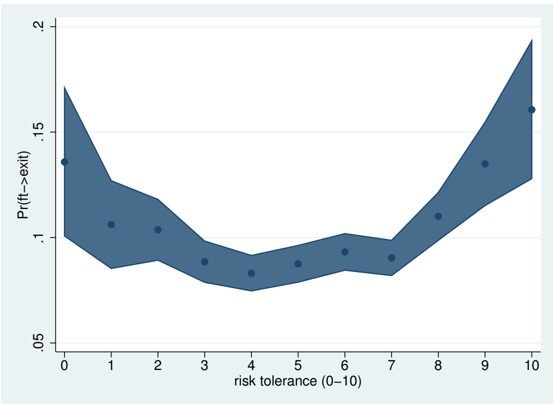
FIGURE A.1: The plots visualize the predicted transition and failure probabilities of part-time(pt) and hybrid self-employed given their respective definition for sample A and B conditional on the risk propensity level. The upper panel depicts the probability of a transition from part-time (left) or hybrid (right) to full-time (ft) self-employment. The lower panel shows failure probabilities of self-employed in part-time mode (left) or hybrid mode (right).



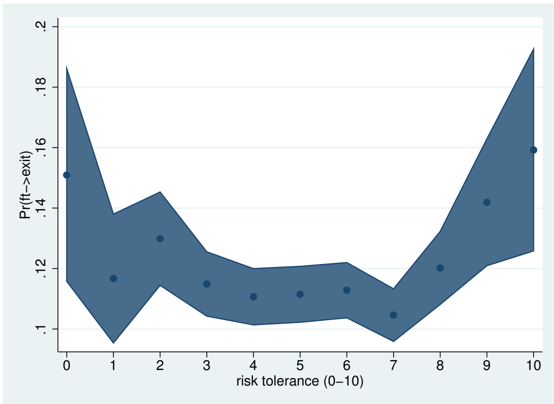
(A) Full-time to part-time transition



(B) Exclusive to hybrid transition



(C) Failure of full-time self-employment



(D) Failure of exclusive self-employment

FIGURE A.2: The plots illustrate the predicted transition and failure probabilities of full-time and exclusive self-employed conditional on risk propensity levels. The upper panel depicts the probability of a transition from full-time (ft) to part-time (pt) on the left and from exclusive (excl) to hybrid self-employment on the right. The failure probabilities of full-time and exclusive self-employed are presented in the lower panel.

Appendix B

B.1 Summary Statisticss, Quarterly Data

	u	v	θ	h	s
sd.deviation	0.384	0.476	0.748	0.428	0.230
autocorrelation	0.424	0.53	0.509	-0.159	0.304
v	-0.515***				
θ	-0.905***	0.767***			
h	-0.783***	0.245	0.691***		
s	0.627***	-0.309	-0.543**	-0.226	

TABLE B.1: Autocorrelation (AC) and Correlation coefficients of the number of unemployed (u) and vacancies (v), the labor market tightness (v/u) and hiring rate (h) and separation rate (s) for the period after first shock and before second shock to the separation rate.(pPlJ= 0.08, baseline: pPlJ= 0.04)

	u	v	θ	h	s
sd.deviation	0.271	0.255	0.471	0.382	0.194
autocorrelation	0.213	0.892	0.536	0.084	-0.165
v	-0.136				
θ	-0.621***	0.669***			
h	-0.597***	0.088	0.334***		
s	0.512***	0.104	-0.341	0.060	

TABLE B.2: Autocorrelation (AC) and Correlation coefficients of the number of unemployed (u) and vacancies (v), the labor market tightness (v/u) and hiring rate (h) and separation rate (s) for the period after the second shock to the separation rate (pPlJ= 0.02, baseline: pPlJ= 0.04)

B.2 The Model in BNG Syntax

The syntax of BioNetGen differs from κ in a few aspects. Besides details in the syntax of rules, the structure of a BNG-model differs slightly because Parameters are assigned names which are then used in the rules. Perturbations to a model can be implemented by stopping the simulation of a model, changing parameter values and restarting the simulation. Here, we omit the description of perturbations in BNG. For details of the BNG syntax, please refer to Faeder, Blinov, and Hlavacek, (2009).

```
begin parameters
 c_init 10
 pJoJ 0.01
 pPlJ 0.04
 pJv 3.2
 p_init 1000
 thou 1000
 mu 1
 beta1 0.9
 pDelay 0.01
end parameters

begin molecule types
 Company(j1,j2,j3,j4)
 Job(l,r,e)
 Person(Emp)
 Dummy(j)
end molecule types

begin seed species
 Company(j1!1,j2!2,j3!3,j4!4).Job(l!1,r,e).Job(l!2,r,e).
         Job(l!3,r,e).Job(l!4,r,e) c_init
 Person(Emp) p_init
end seed species

begin observables
 Molecules Jobs_tot Job()
 Molecules Jobs_occ Job(e!1).Person(Emp!1)
 Molecules Person_uemp Person(Emp)
```

```
 Molecules Jobs_free Job(e)
end observables

begin functions
 LMtight()=if(Person_uemp>0, Jobs_free/Person_uemp, 0)
 MatchP()=if(Person_uemp>0,
          if(Jobs_free/Person_uemp<0.01,
            mu*(Person_uemp)^(beta1-1)*(Jobs_free+1)^(-beta1),
            mu*(Person_uemp)^(beta1-1)*(Jobs_free)^(-beta1)),0)
 Vac_creating()=if(Jobs_free>0,
                     if(Person_uemp/Jobs_free>pJoJ,
                        pJoJ, Person_uemp/Jobs_free),
                     Person_uemp/(Jobs_free+1))
end functions

begin reaction rules
 #'Job offers job':
  Job(l!+,r,e!+)-> Job(l!+,r!1,e!+).Job(l!1,r,e)
   Vac_creating()
 #'Person gets job'
  Job(l!+,e) + Person(Emp)-> Job(l!+,e!1).Person(Emp!1)
       MatchP()
 #'Person lose job'
  Job(e!1).Person(Emp!1)-> Job(e!1).Dummy(j!1) +
   Person(Emp) pPlJ
  Job(e!1).Dummy(j!1) -> Job(e) pDelay DeleteMolecules
 #'Job vanishes'
  Job(r!1).Job(l!1,e,r)-> Job(r) pJv DeleteMolecules
end reaction rules

begin actions
 simulate_nf({
      t_end=>2000,suffix=>nf,
      n_steps=>2000,param=>"-ogf -gml 500000"
      });
end actions
```

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Erklärung

Hiermit erkläre ich, KATJA HILLMANN, dass ich mich noch keiner Doktorprüfung unterzogen oder um Zulassung zu einer solchen beworben habe.

Die Dissertation mit dem Titel

“Transitions between Employment, Unemployment and Entrepreneurial Activities – Evidence from Germany“

hat noch keiner Fachvertreterin, keinem Fachvertreter und keinem Prüfungsausschuss einer anderen Hochschule vorgelegen.

Unterschrift: ______________________________

Ort, Datum: ______________________________