Three essays in microeconometric methods and applications

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Summary

This thesis comprises three essays. The first two make use of individual-level data on British workers from the British Household Panel Survey to study different aspects of non-standard employment.

The first essay, co-authored with Mark Bryan, presents estimates of the implicit monetary value that workers attach to non-standard work. We employ and compare two alternative methods to measure workers' willingness to pay for four non-standard working arrangements: flexitime, part-time, night work, and rotating shifts. The first method is based on job-to-job transitions within a job search framework, while the second is based on estimating the determinants of subjective well-being. We find that the results of the two methods differ, and relate them to conceptual differences between utility and subjective wellbeing proposed recently in the happiness literature.

The second essay builds on economic theories of consumption and saving choices to investigate whether workers expect temporary work to be a stepping stone towards better jobs, or a source of uncertainty and insecurity. The evidence provided shows that temporary work entails both expected improvements in future earnings, and uncertainty. Households' consumption and saving choices are used to assess which of these two effects is prevailing, providing an alternative empirical approach to measure the consequences of temporary work for workers' welfare. The results suggest that a stepping stone effect towards better jobs is present and, more importantly, is perceived by individuals and internalized in their behaviour.

nally, the last essay has a specific focus on econometric methods. A Monte Carlo experiment is used to investigate the extent to with the Poisson RE estimator is likely to produce results similar to ones obtained using the Poisson FE estimator when the random effects assumption is violated. The first order conditions of the two estimators differ by a term that tends to zero when the number of time periods (T), or the variance of the time-constant unobserved heterogeneity (V), tend to infinity. Different data generating processes are em-

ployed to understand if this result is likely to apply in common panel data where both characteristics are finite. As expected, the bias of RE estimates decreases with T and V. However, the same does not hold for the estimated coefficient on the time invariant dummy variable embedded in the conditional mean, which remains substantially biased. This raises a note of caution for practitioners.

Declarations

No part of this thesis has been submitted for another degree.

Chapter 1 is a joint work with my former supervisor Dr. Mark Bryan (currently at University of Sheffield), the remaining two chapters are exclusively mine.

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Contents

Chapter 1

Non standard work: what's it worth? Comparing alternative measures of workers' marginal willingness to pay

Introduction

A job is about much more than earning a wage. Jobs differ widely in characteristics such as the type of work they involve, the number of hours required, the timing of shifts and the amount of flexibility. In a competitive labour market, compensating wage differentials should arise that equalise workers' utility across jobs - so that wages are higher for jobs with undesirable characteristics and lower for jobs with good characteristics (Rosen, 1987). In principle, compensating differentials estimated from hedonic wage regressions can then be used to infer how much workers are willing to pay in order to avoid (or to gain) a particular characteristic: their marginal willingness to pay (MWP). In practice, there are substantial challenges to identifying hedonic equations because workers and firms are matched endogenously (Lang and Kahn, 1990), there may be unobserved confounding factors such as individual ability, and labour markets may deviate from the competitive ideal (Hwang et al., 1998). As a result, two alternative methods have become increasingly popular. The first, based on revealed preference, looks at job transitions to see whether workers leave bad jobs at a faster rate than good jobs. The second method, based on workers' assessments of their well-being, compares reported well-being in good and bad jobs.

In this paper we compare these two methods in estimating the MWP for non-standard work arrangements in the British labour market. We find that they deliver substantially different results, which we argue derive from the distinct conceptual basis of each measure. Performing further tests, we conclude that our findings are consistent with a recent literature arguing that people trade off their well-being against other objectives when making choices. Thus the value (MWP) of non-standard work expressed through job choices is different from its value in terms of subjective well-being, and this distinction should be explicitly recognised when presenting MWP estimates.

Our work makes several contributions. Methodologically, we provide a comparison of the two alternative MWP measures, estimated using the same sample of individuals (thus our results are informative of the likely differences in MWP estimates that researchers may find in practice). In addition we link differences in the two measures to conceptual differences between utility and subjective wellbeing that have been validated in recent experimental studies. We thereby contribute to the debate about the measurability of utility and the empirical value of indicators of subjective well-being. An implication of the new literature on utility and subjective wellbeing is that there is not a single representation of MWP: utility trade-offs (revealed by choices) need not be the same as wellbeing trade-offs . We find, for example, that a part-time job would deliver the same amount of job satisfaction as a full-time job even if workers had to sacrifice most or all of their income; however workers tend to quit part-time jobs with earnings that are substantially less than pro-rata. This indicates that earnings matter to part-time employees (as revealed by their quitting behaviour) over and above their level of job satisfaction. We similarly find some evidence that workers require a smaller premium to compensate them for the dissatisfaction of working at night than is required to stop them from quitting night work. Overall, we provide new evidence about workers' preferences over the amount and timing of the work they do, suggesting that workers care particularly about their number of weekly hours and about working rotating or night shifts.

We are aware on another contribution in the literature related to ours. Akay et al. (2015) compare the income-leisure preferences revealed by labour supply choices with preferences implied by SWB equations. They conclude that preferences coincide on average, although they differ among some sub-populations who may be subject to choice constraints or optimisation errors. Our work differs on some dimensions. While the focus in Akay et al. (2015) is on income-leisure preferences, we provide estimates of MWP for a wider set of job attributes. More importantly, we derive revealed preferences based MWP from job search model which implies dynamic optimization, rather than a static labour supply model. Similarly to the authors we do find similarities between the two approaches, at least with respect to the sign on the implied MWP. However the test we present in Section 1.5 suggests a stronger conclusion about conceptual differences between SWB-based and revealed-preferences based measures of MWP.

The chapter is structured as follows. Section 1.1 presents the background of the paper, providing a brief introduction for the two methodologies. Section 1.2 introduces non standard working arrangements, the data we use for the empirical analysis, and presents some descriptive statistics. Sections 1.3 and 1.4 present, respectively, the revealed preferences approach and the SWB approach, describing the respective theoretical frameworks and estimation approaches. Results are also presented. A possible explanation for our different findings is discussed in Section 1.5. Section 1.6 concludes.

1.1 Background

The work of Rosen (1974) laid the foundations for the study of hedonic markets, in which the prices of differentiated products reflect the characteristics embodied in those products. Applying these ideas to labour markets, Rosen (1987) showed that in a perfectly competitive setting with many firms and workers, each job characteristic is priced in an implicit market. In such an environment workers choose their job, defined as a wage and a set of characteristics, by maximizing their utility subject to the constraint of the hedonic wage curve. In equilibrium, differences in the wages of otherwise homogeneous workers can be interpreted as equalizing differences that compensate workers (at the margin) for accepting specific undesirable job characteristics (or "penalise" them for enjoying desirable characteristics). Since Rosen's early work many researchers have attempted to measure these compensating differentials using hedonic wage equations. However, it has proved remarkably difficult to find compensating differentials that are consistent with reasonable expectations about workers' MWP: estimates are often insignificant, or of unexpected sign. A common explanation is that more productive workers select into jobs with better characteristics, thus biasing estimates of wage differentials towards zero, but even studies that control for unobserved productivity using individual fixed effects often fail to find plausible compensating differentials (Brown, 1980). More generally, identification of wage differentials from hedonic equations is a challenge owing to the endogenous matching of workers and firms (Lang and Kahn, 1990).[1]

Compensating differentials may also be difficult to find in the real world if labour markets are not be perfectly competitive. The theory of compensating differentials assumes a frictionless labour market in which workers have full information about available jobs and can move costlessly - to prevent a worker quitting a job, any disamenity must be fully com-

[1] Rosen (1974, 1987) stressed that wage differentials only identify the preferences of those agents who are on the margin of choice. For instance most workers in clean jobs would require more than the equilibrium wage differential to work in a dirty job (this is why they chose a clean job) and vice versa. So the wage differential will not generally equal average MWP. Only if workers have identical preferences will the wage differential equal MWP.

pensated by a higher wage. But in a labour market with search frictions or costly mobility, wages will not necessarily compensate for job disamenities (Hwang et al., 1998; Lang and Majumdar, 2004). Job quality may vary among identical workers, with "good" jobs paying both higher wages *and* having better characteristics. Thus hedonic prices in a frictional labour market may diverge from workers' MWP.

Given the difficulties of measuring MWP using hedonic wage regressions, two alternative methods have become popular. The first, developed by Gronberg and Reed (1994), is explicitly embedded in an environment of incomplete information and search frictions. The idea behind their approach is that the utility trade-off between wage and other job attributes influences job durations: workers will stay longer in jobs with higher wages and good attributes. Job separations in such a framework are then informative about workers' preferences for wage and job attributes. Gronberg and Reed estimate workers' MWP for various job attributes applying duration analysis to job spell data from the National Longitudinal Survey Youth Cohort. The same approach is followed by others, including Van Ommeren et al. (2000), who demonstrate the validity of this approach even in the case of a more general characterization of the search environment with respect to the one adopted by Gronberg and Reed (1994), and estimate workers' MWP for commuting using Dutch panel data.

The second method of measuring MWP is based on the idea that if we were able to observe workers' utility on the job, then we could directly estimate the effects of wages and job attributes. In the absence of measures of utility, researchers have turned to data on self-reported subjective wellbeing (SWB) as a proxy for utility. This has led to a stream of research in areas ranging from health to labour economics that uses the so-called income compensation methodology to value non-financial goods in terms of the amount of income required to hold SWB (utility) constant [2]. The appealing simplicity of this approach comes at the cost of strong assumptions about the relationship between utility and SWB indicators,

[2] See Dolan et al. (2011) for a survey.

which we discuss in detail in section 1.5. Nevertheless, following the SWB approach, workers' MWP for job amenities can be estimated from an equation to explain SWB as a function of the wage, job amenities and other controls.

The measure of SWB that we focus on is job satisfaction. Hamermesh (1977) pioneered its use as an economic variable and many other studies have since shown that job satisfaction is a predictor of job quits (see among others Freeman 1978; Clark 2001; Lévy-Garboua et al. 2007; Green 2010). While many economists are still sceptical that job satisfaction, and SWB more in general, can be taken as a proxy for utility, Hamermesh (2001) concludes that even given the limitations outlined by many authors, job satisfaction might still be regarded as a key indicator of how workers perceive their job as a whole in relationship to different opportunities in the labour market.

We estimate workers' MWP for non-standard working arrangements in Britain using both the job search approach and the SWB method. In both cases we use the most recent techniques from the applied literature - thus our results are informative of the likely differences in MWP estimates that researchers may find in practice. Estimates under the job search approach are obtained using mixed proportional hazard models with exponential parametrizations and allowing for unobserved heterogeneity. Estimates following the SWB approach are obtained using job satisfaction equations allowing for individual fixed effects. We find that estimates obtained differ across the two methodologies, suggesting that that two measures correspond to distinct concepts. We explore theoretically the differences between the two approaches building on recent contributions to the life satisfaction literature.

1.2 Non standard work and the British Household Panel Survey

Standard work is generally identified with the traditional "9-to-5" five days workweek. However, alternative working schedules are widespread in modern labour markets. Differences between standard and non-standard workers emerge not only with respect to total amount of hours spent at the workplace, but even in respect of the time of the day people usually work. Moreover, new types of working agreements allowing for higher schedule flexibility, like flexitime, are increasingly available.

We focus on the following dimensions of non-standard work: short or long hours, working at night, rotating shifts, and flexible work. In order to capture variability in the total amount of hours spent at work, following Booth and van Ours (2008), we define a set of dummies which identify jobs characterized by, respectively, 1-15, 16-30, 31-48, and more than 49 weekly hours. This classification takes into account the potential effects of some features of the British welfare system on labour supply choices. The first category has a cut-off at 15 hours because workers below this threshold are not eligible for main work-contingent benefits and tax credits, but are entitled to other forms of income support. With respect to the second category, 30 hours per week is the threshold generally used in the literature to identify part-time work, and is also the minimum amount of hours required to be eligible for in-work benefits for individuals aged 25-59. Lastly, 48 hours a week is the maximum number of hours individuals are allowed to work according to the "working time directive". Individuals who choose to work to work more than 48 hours need to opt-out from working time regulations.

Focusing on the time of the day people actually work, we identify three categories: people working during the daytime, at night, and in rotating shifts. Finally we identify those jobs characterized by flexible arrangements, defining a dummy for flexitime contracts - the most common type of flexible agreement - and a dummy for the residual categories (annualised hours, term time only, job share, nine day fortnight, 4 1/2 day week, zero hours contract).

Working fewer hours is generally associated with an increased work-life balance, while the opposite holds true for working schedules which entail long hours. A similar argument can be made regarding flexible agreements. They are designed to give workers more control over the working schedule by allowing them to "fine-tune" the time they spend on the job with respect to their out-of-work life. In contrast, night shifts and rotating shifts are likely to be perceived by workers as "bad" working conditions. Indeed, working at night, or being subject to rotating shifts, may adversely affect the work-life balance of workers given the low level of flexibility they allow for.

Our empirical analysis is carried out using data from British Household Panel Survey (BHPS), a nationally representative longitudinal study run between 1991 and 2008. The original BHPS sample covers roughly 10,000 individuals in 5,500 households in Great Britain.[3] The information collected within the survey spans a variety of topics both at the household and individual level, including household composition, individual socio-demographic characteristics, employment status and history, values, health, time use, and satisfaction.

The richness of details about individuals' job makes the BHPS a perfect source of information for the task of this analysis. Specifically, every year individuals are asked to report a variety of characteristics of their current job, including monthly earnings, number of hours worked, times of day individuals usually work, particular flexible agreements (from interview wave 9), overall level of job satisfaction, and satisfaction with specific job facets - pay, hours of work, security, promotions prospects, relations with supervisor, use of own initiative.

Importantly, BHPS data also contains information about individual labour market spells (both employment and non-employment spells), including their start date and the reason for the end of the terminated spell. This latter characteristic is fundamental in our setup, given it allows to disentangle voluntary job quits from separations which happened for

[3] Between 1991 and 2008 four extension samples have been added to the original 1991 sample: ECHP extension (waves 7-11), Welsh extension (waves 9-18), Scottish extension waves (waves 9-18), Northern Ireland extension (waves 11-18). By referring to the BHPS in this paper we refer to the full BHPS sample, including these extensions. Since longitudinal weights (accounting for differential non-response, including attrition) are available only for the original 1991 sample, all the regressions in this paper are unweighted. This might raise concerns about the potential bias induced by unequal sampling probabilities and non-response. As stated by Solon et al. (2015), regression estimates are biased if sampling and non-response are not independent of the dependent variable conditional on the explanatory variables. The inclusion of region and wave dummies in all regression models should address the issue of unequal probabilities due to the extension samples. Non-response, instead, is not issue to the extent that, conditional on the set of covariates, data are missing completely at random.

other reasons.

Information about the current activity at the time of interview is recorded separately from information about inter-wave labour market spells (covering the time span between September a year before and the interview date). These two sources can be combined using the sequence of start dates (measured to the nearest month) in order to obtain continuous-time spell data for consistent individual work-life histories. An example, using wave 10 of the survey, helps to better understand how information about spells is recorded in the BHPS. Interviews for wave 10 were held between September 2000 and May 2001. At the time of interview respondents were asked if their current labour force status began after 1 September 1999. If so, they were asked information about each of the (potentially multiple) spells between 1 September 1999 and the date of the interview, including the start date of each of these spells. If an individual was also interviewed in 1999, the start date of the oldest recorded spell after 1 September 1999 overrides the start date of the current status in 1999, and the start date of the subsequent spell provides its end date. In order to deal with issues of recall bias, overlapping dates, and seam effects, we combined inter-wave job histories and main-interview data using a revised and updated version of the code developed by Mare (2006) (see also Halpin, 1997). The resulting dataset contains both multiple spells per individual, and multiple observations per spell (i.e. a spell can span multiple interviews).

Since our objective is to estimate a model for job-to-job transitions, after having obtained a dataset of consecutive labour market spells, we include in our estimation sample only job spells (i.e. we exclude unemployment and inactivity spells). Consistently with previous literature, we further restrict our estimation sample to individuals aged 16-65 who: i) are in paid employment ii) are not in full-time education or further education; iii) are not self-employed; iv) have no missing values in any of the relevant characteristics.

We also exclude short job spells starting after the interview date, and ending before the subsequent one (i.e. job spells that do not span an interview date). These spells are excluded because information about most dimensions of non-standard work is recorded only for the current job at the time of interview. As a result, only spells that can be matched with interview dates can provide useful information.

Imposing the above restriction, we obtain an estimation of 5,130 individuals in 12,330 spells. However when we focus of flexitime and other flexible agreements we are constrained to use only the last nine waves of the BHPS in which the relevant information was collected (3,384 individuals in 6,184 spells).

Descriptive statistics for the full set of variables we use in our models are presented in table 1. Average log monthly earnings are approximately £1,340. While the majority of workers in our sample (64%) is characterized by the "traditional" working schedule of approximately 40 hours per week, the fraction of individuals working short and long hours is far from negligible. 1-15 hours schedules are present in 5% of our sample, "standard" part-time (16-30 hours) and long hours (49 + hours) are present in, respectively, 15% and 16% of cases. 9% of individuals has jobs which entail working at night, while the rotating shifts characterize 7% of the sample. Flexitime is the most spread form of flexible arrangements, 15%[4].

These fractions are fairly stable across waves, although the share of individuals working long hours is decreasing after 1998 (year of the introduction of the working time directive) , and a gradual increase characterizes the fraction of individuals working 16-30 hours after 2002.

Not surprisingly, data shows some degree of heterogeneity in the prevalence of non-standard work between men and women. More specifically, the incidence of part-time work, measured as the fraction of individuals working either 1-15 hours or 16-30 hours, is much more pronounced for women than men, while the opposite holds true for long hours, and to some degree for rotating shifts. No heterogeneity is, instead, present with respect to flexible work arrangements and night work.

Overall job satisfaction is derived from individuals' answers to the following question: *"All*

[4]The fraction is calculated on the 9-18 waves sample.

things considered, how satisfied or dissatisfied are you with your present job overall?". It is measured on a Likert-type scale ranging from 1, "not satisfied at all", to 7, "completely satisfied", and exhibits a sample mean equal to 5.36.

Table 2 shows the distribution in our sample of the reason why the job spell was terminated which allows to disentangle voluntary job to job transitions ("left for better job") from separations which happened for other reasons (all the remaining categories). It is worth noting that voluntary job quits are the most frequent type of separation in the data, account for the 25% of them.

Table 1.1: Descriptive statistics

VARIABLES	Mean	Std. Dev.	Min	Max
Log of real monthly earnings	7.19	0.71	2,81	8,93
Hours: 1-15	0.05	0.22	0	1
Hours: 16-30	0.15	0.35	0	1
Hours: 31-48	0.64	0.48	0	1
Hours: 49+	0.16	0.37	0	1
Night shifts	0.09	0.28	0	1
Rotating shifts	0.07	0.26	0	1
Flexitime*	0.15	0.36	0	1
Other flexible agreements*	0.03	0.18	0	1
Female	0.50	0.50	0	1
Pre-school children	0.11	0.31	0	1
Age	38.26	11.78	16	65
Never married	0.30	0.46	0	1
Married	0.59	0.49	0	1
Separated	0.10	0.30	0	1
Widowed	0.01	0.11	0	1
Education: primary\lower secondary	0.16	0.37	0	1
Education: upper secondary	0.46	0.50	0	1
Education: higher education	0.38	0.49	0	1
Occup.: large employers & higher management	0.04	0.20	0	1
Occup.: higher professional	0.07	0.26	0	1
Occup.: lower management & professional	0.29	0.45	0	1
Occup.: intermediate	0.19	0.39	0	1
Occup.: lower supervisory & technical	0.12	0.33	0	1
Occup.: semi-routine	0.16	0.37	0	1
Occup.: routine	0.13	0.33	0	1
Firm size: <25	0.34	0.47	0	1
Firm size: 25-99	0.25	0.43	0	1
Firm size: 100-499	0.24	0.43	0	1
Firm size: >499	0.17	0.38	0	1
Union recognition at the workplace	0.49	0.50	0	1
Job satisfaction: overall	5.36	1.30	1	7
Observations	33,959			

Notes: Regional (20), Industry (9), and Wave (18) dummies are excluded for brevity. *Statistics for Flexitime and Other flexible arrangements are to waves 7-18 (16,092 observations)

Table 1.2: Reason for leaving the current job

Reason for leaving the job	**N. of ended spells**	**% of ended spells**
Promoted	2,261	24.26
Left for a better job	2,334	25.04
Redundant	1,150	12.34
Dismissed	161	1.73
Temp. job ended	433	4.65
Retirement	373	4.00
Stopped for health reasons	255	2.74
Stopped for family reasons	303	3.25
Other	2,050	22.00
	9,320	100.00
	Total N. of spells	**% of total spells**
Ended spells	9,320	75.59
Ongoing spells	3,010	24.41
Total	12,330	100

1.3 Deriving MWP from job-to-job transitions

A methodology to estimate MWP from job durations was first developed by Gronberg and Reed (1994). The basic idea is that in a dynamic search environment differences in job durations are informative about the relative weights of job characteristics in workers' utility functions. Extending Gronberg and Reed's methodology, Van Ommeren et al. (2000) describe how the theoretical model applies under a more generic search environment, and calculate workers' MWP for commuting using Dutch data. In the same spirit Van Ommeren and Fosgerau (2009) compare MWP for commuting time obtained using job moving behaviour with estimates obtained using workers' search behaviour as an identification strategy. Other applications include estimation of MWP to avoid night shifts - Manning (2003) - and estimation of MWP for job attributes using data on maternity leave in Germany - Felfe (2012). Bonhomme and Jolivet (2009) use job durations to estimate MWP for non-wage characteristics. Using data from the European Community Household Panel (ECHP) they find significant MWP for most job amenities, but they demonstrate that the estimates differ from those implied by a cross-sectional regression of wages on non-wage characteristics.

Dale-Olsen (2006) uses Norwegian matched employer-employee data to estimate MWP for safety comparing hedonic wage, quit and job duration models, while Dey and Flinn (2008) estimate the MWP for health insurance coverage using US data from Survey of Income and Program Participation (SIPP).

1.3.1 Theoretical framework

Under the assumption of a perfectly competitive labour market, a standard cross-section hedonic wage regression is able to represent a long-run equilibrium relationship between wage and non-wage characteristics. However, Hwang et al. (1998) demonstrate how estimates of MWP derived from hedonic wage regressions are likely to be biased within a dynamic framework characterized by job search and an equilibrium wage dispersion. They show that, if firms differ in the cost of providing non-wage characteristics, those firms which face higher costs will offer lower wages and worse working conditions in equilibrium. Firm heterogeneity would act as an unobservable disturbance term in a hedonic wage regression, and it would likely be correlated with job characteristics of interest. This would bias estimates of workers' MWP for amenities and disamenties. Gronberg and Reed (1994) develop and apply a new methodology in order to estimate workers' MWP starting from a simple model of on-the-job search, as developed by Mortensen (1987).

Suppose that individuals have jobs characterized by (w,X) - the wage, w , and a set of non-wage characteristics, X. While on their job, they receive new job offers from firms. New offers arrive according to a Poisson process at rate λ. On the other side, workers face a probability of being laid off, δ, at each point in time. This latter involuntary separation rate is assumed to be independent of wage and job characteristics within the model. This assumption, although rather restrictive, is crucial in order to estimate workers' MWP. Job offers at every point in time are random draws from the joint cumulative distribution of wage and job attributes, $F(w^*,X^*)$, faced by workers of given productivity in the labour market. Workers are assumed to know both the arrival rate λ, and the joint cumulative distribution $F(w^*,X^*)$, but the timing of realization, and the characteristics of the specific offer are unknown. Every job delivers to the worker the instantaneous utility flow $u(w,X)$, which depends on both the wage and non-wage characteristics. Job mobility is driven by dynamic optimization, this is to say that workers decide whether to change their job when facing a new offer by maximizing the expected present value of utility over an infinite horizon. Defining $V(w,X)$ to be the expected present value of utility of the current job with characteristics w and X, and $V(w^*,X^*)$ the value function of the alternative potential offer, workers accept a new job when:

$$V(w^*,X^*) > V(w,X) \tag{1.1}$$

Given that, according to the model, the search environment does not change when accepting a new offer, the only change within the value function is the instantaneous utility flow $u(w,X)$. The condition expressed by equation (1.1) is, then, equivalent to:

$$u(w^*,X^*) > u(w,X) \tag{1.2}$$

The total exit rate out of the current job can be expressed as:

$$\theta(w,X) = \delta + \lambda\left[1 - F\left(u\left(w,X\right)\right)\right] \tag{1.3}$$

The above expression describes the total exit rate as the sum of the probability of an involuntary separation plus the probability of quitting. The latter can be further decomposed into two components, namely the probability of receiving a new offer, λ, and the probability that the offer received is acceptable for the worker, $[1 - F(u(w,X))]$. $F(u(w,X))$ is the cumulative distribution of the random variable $u(w^*,X^*)$ obtained from the joint distribution $F(w^*,X^*)$, evaluated at the current job values, (w,X). It represents the probability that the offer delivers an higher instantaneous utility, triggering a job-to-job transition.

Differentiating equation (1.3) with respect to w, and the generic job attribute x within the vector X we get:

$$\frac{\partial\theta(w,X)}{\partial w} = -\lambda\frac{\partial F\left(u(w,X)\right)}{\partial u(w,X)}\frac{\partial u(w,X)}{\partial w} \tag{1.4}$$

$$\frac{\partial\theta(w,X)}{\partial x} = -\lambda\frac{\partial F\left(u(w,X)\right)}{\partial u(w,X)}\frac{\partial u(w,X)}{\partial x} \tag{1.5}$$

Taking the ratio of these two terms:

$$\frac{\partial\theta(w,X)/\partial x}{\partial\theta(w,X)/\partial w} = \frac{\partial u(w,X)/\partial x}{\partial u(w,X)/\partial w} \tag{1.6}$$

The right-hand side of the above equation describes workers' MWP, i.e. the rate at which a worker would be willing to trade the wage against a generic non-wage attribute x. Given δ does not depend on w and X by assumption, MWP can be obtained by looking at the ratio of marginal effects of x and w on the hazard rate for job-to-job transitions.

1.3.2 Reduced-form duration model specification

In our empirical specification we assume that the length of a job spell up to a job-to-job transition follows an exponential distribution with a constant hazard rate, $h(w,X)$, which depends on current job characteristics. Following Van Ommeren et al. (2000) we assume this hazard rate has an exponential parametrization, and can be written as follows:

$$h(t|\nu_i, Z_i) = \exp(Z_i'\beta)\cdot\nu_i \tag{1.7}$$

where Z_i is a vector of individual and job characteristics, including the vector X_i - and ν_i, an unobserved random variable capturing worker heterogeneity. The inclusion of ν_i in the model is crucial in order to get consistent estimates of the parameter vector β, as pointed out by Lancaster (1990). The sample we use in order to estimate the duration model for job-to-job transitions consists of 5,130 individuals in 12,717 spells, using waves 1-18 of the BHPS. When we focus on flexitime and other flexible agreements, however, we are constrained to use data only for waves 9-18 in which the relevant information was collected. Our data consist of both multiple spells and multiple observations within each spell - each observation corresponding to a wave of the BHPS. The vector Z_i includes a range of controls: age, gender, education level, family status, union recognition at the workplace, firm size, industry, regional, and social group dummies. Since a job spell may span more than one interview date, job attributes and individual characteristics are allowed to vary annually within the spell (as in Van Ommeren et al. 2000). A spell is defined as the length of time until a voluntary job-to-job transition.

Following Van Ommeren et al. (2000), job spells terminated for reasons other than a voluntary quit, as well as those spells which are ongoing at the time of the last interview, are treated as right-censored observations of the duration until a job-to-job transition, Left-censoring is, in principle, not an issue given our estimation sample contains only spells for which start dates are available that can be matched with interview dates.

Although treating other types of transitions as uninformative censoring might seem restrictive from an empirical perspective, this choice is driven by the assumptions of the search model. If the hazard rate for these transitions is allowed to depend on w and X, the search-theoretical predictions on the effect of w and X on the job-to-job transition rate would be violated.

Intuitively, MWP can be recovered from partial effects of job attributes on transition rates only to extent that current job attributes enter the model solely via the instantaneous utility flow, and not through other parameters of the search environment.

Duration models of the type expressed by equation (1.7) are knows as parametric "shared frailty model" (Gutierrez, 2002 and Cleves et al., 2008). The frailty term ν_i reflects worker-specific heterogeneity in duration variation. The duration unconditional on ν_i is then obtained by integrating out this component, assuming that it follows a Gamma distribution with mean 1 and variance θ (to be estimated from the data). The model is estimated via Maximum Likelihood. Kaplan-Meier estimates of the empirical survivor function by groups defined by our characteristics of interest are presented in Appendix 1.

One caveat to bear in mind concern the interpretation of the estimated effects of job attributes on the hazard rate of job-to-job transitions. The suggested estimation method corrects only for time invariant heterogeneity among workers, which is independent on observable characteristics. This leaves open issues such as sorting into jobs with specific job attributes which cannot be tackled with random effects models. To the extent that sorting into jobs depends on individual preferences potentially correlated with the decision to move to another job, conditional on observable characteristics, the coefficients of the duration model will provide a biased estimate of the true causal effect of the job attributes on the hazard rate of job-to-job transitions. There is, however, no clear indication about the direction of this bias.

1.3.3 Estimates of MWP from duration model

Tables 1.3 and 1.4 present, respectively, the estimated coefficients of our duration models and the associated MWP. Estimated MWP are obtained according to the following formula:

$$MWP_x = \exp\left(-\frac{\hat{\beta}_x}{\hat{\beta}_{lnw}}\right) - 1 \tag{1.8}$$

where $\hat{\beta}_x$ is the coefficient associated with the dummy indicating the generic non-wage attribute x, and $\hat{\beta}_{lnw}$ is the coefficient associated with the log of real monthly earnings.

We derive MWP after making two modifications to the methodology presented above. First, as is standard in the MWP durations literature (see Van Ommeren et al. 2000; Gronberg and Reed 1994) the wage enters Z_i in the hazard function in log form. This leads naturally to an expression for MWP as a percentage of wages, which may be preferred to a measure in monetary units. Second, it is necessary to alter the formula for MWP implied by equation (1.6) given the discrete nature of the job characteristics under consideration. Let x_i take value 1 if a job characteristic is present and 0 otherwise.

We then define the MWP as the (percentage or proportionate) amount of wages which a worker would be prepared to give up in order to enjoy an amenity; or the amount they would need to receive in order to accept a disamenity.

Consider the two wages (w_0 and w_1) which hold utility, and hence the hazard rate, constant, first without the characteristic and then with it:

$$h(t|\nu, Z, ln(w_0), x = 0) = h(t|\nu, Z, ln(w_1), x = 1) \tag{1.9}$$

where Z now includes all characteristics except $ln(w)$ and x (the i subscript is dropped for simplicity). If x represents an amenity, then w_1<w_0 and vice versa if it is a disamenity. From equation (1.7), we can write:

$$\exp(Z'\beta + \beta_{lnw} ln(w_0)) \cdot \nu = \exp(Z'\beta + \beta_{lnw} ln(w_1) + \beta_x) \cdot \nu \tag{1.10}$$

which simplifies to:

$$\beta_{lnw} ln(w_0) = \beta_{lnw} ln(w_1) + \beta_x \cdot \tag{1.11}$$

Hence, the difference in log wages is:

$$ln(w_1) - ln(w_0) = ln(w_1/w_1) = -\beta_x/\beta_{lnw} \tag{1.12}$$

which is equivalent to the proportionate change of:

$$MWP_x = \frac{w_1 - w_0}{w_0} = \left(-\frac{\beta_x}{\beta_{lnw}}\right) - 1 \tag{1.13}$$

Table 1.3: Duration model for job-to-job transitions: estimated coefficients

	Waves 1-18		**Waves 9-18**	
	(1)	**(2)**	**(3)**	**(4)**
Real monthly earnings (log)	-0.604***	-0.337***	-0.558***	-0.190**
	[0.046]	[0.057]	[0.072]	[0.087]
Hours: 1-15	-0.842***	-0.208	-0.807***	-0.007
	[0.135]	[0.134]	[0.217]	[0.210]
Hours: 16-30	-0.513***	-0.091	-0.564***	0.031
	[0.083]	[0.082]	[0.122]	[0.119]
Hours: 49 +	0.251***	0.105*	0.218**	0.150
	[0.065]	[0.062]	[0.102]	[0.095]
Work at Night	0.324***	0.176**	0.280**	0.137
	[0.076]	[0.071]	[0.111]	[0.102]
Rotating Shifts	0.037	0.097	-0.169	0.010
	[0.092]	[0.087]	[0.165]	[0.154]
Flexitime			-0.082	0.069
			[0.105]	[0.099]
Other Flexible			-0.196	0.056
			[0.160]	[0.162]
Additional controls	no	yes	no	yes
Observations	33,959	33,959	16,092	16,092
Number of individuals	5,130	5,130	3,384	3,384
Number of spells	12,330	12,330	6,184	6,184

Notes: Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Additional controls included in all equations: gender dummy; age; age squared; family status dummies (3); dependent children dummy; education dummies (2); firm size dummies (3); union at the workplace dummy; region dummies (17); industry dummies (8) occupation dummies (6); wave dummies (17). The full set of results is provided in the Appendix 1

The first two columns of table 1.3 use observations from waves 1-18 of the BHPS. We refer to these results when considering the effects of working hours, rotating shifts and night shifts. The last two columns show evidence from waves 9-18 of the BHPS in which the relevant information concerning flexible agreements was collected. We refer to this evidence when considering flexitime and other flexible agreements. In column 1 quits are modelled as a function of our key explanatory job characteristics only. They are all highly statistically significant with the exception of rotating shifts. However, when we include relevant individual and other job-related attributes (including a full set of dummies for regions, industry and socio-economic status) in column 2, the magnitude of the coefficients associated with the key explanatory variables dramatically drop, with only night shifts and overtime remaining significant at conventional levels. Looking at the sign of coefficients in this column, they are (more or less) in line with our expectations. Workers with high monthly earnings or short hours are more likely to have longer durations before they quit for a better job. The opposite holds true for workers working long hours, working at night or in shifts. The coefficients on the control variables (presented in appendix) indicate that job durations are longer for women, people with low levels of education and for those jobs where unions are recognized at the workplace. Conversely individuals experiencing shorter durations before a job-to-job transition are those with higher levels of education, single or separated. Focusing on flexitime and other flexible agreements, coefficients in column 3 and 4 suggest that these types of job are associated with shorter durations, however the estimates are very imprecise.

All the models have been also estimated allowing for gender heterogeneity of the effects of the different characteristics, by interacting the main characteristics of interest with a dummy variable for gender. We also considered a triple interaction term with the indicator variable for dependent children, potentially important for part-time women. While the main effects remained significant, none of these interactions turned out to be statistically significant in our analysis.

We now turn to MWP for non-standard work implied by these coefficients (table 1.4). MWP is interpreted as the percentage of the real monthly earnings that workers are willing to trade off, on average, for each of our job characteristics of interest, in order to hold utility fixed. Standard errors are obtained using the delta method.

Table 1.4: MWP estimates using job-to-job transitions

	MWP	**S.E.**
Hours: 1-15	-0.460**	0.185
Hours: 16-30	-0.237	0.173
Hours: 49+	0.367	0.25
Work at Night	0.688*	0.389
Rotating Shifts	0.335	0.346
Flexitime	0.436	0.787
Other Flexible	0.340	1.158

Notes: *** p<0.01, ** p<0.05, * p<0.1. MWP's are expressed as fraction of real mothly earnings. MWP's for each characteristic are obtained using coefficients from table 1.3, column 2. MWP's for Flexitime and Other Flexible are obtained using coefficients from the same table, column 4. Standard Errors are obtained using Delta Method

Statistically significant MWP are found only for night shifts, and for those jobs at the low extreme of the weekly hours distribution: less than 15 weekly hours per week. Our estimates suggest that "traditional" full time workers would be willing to take a monthly earnings cut of 46% if their hours were cut to 15 hours per week or less (or alternatively they would not be willing to work more than 15 hours per week if their monthly earnings were reduced by 46%). This results, together with the (non-significant) positive MWP for long hours, may be interpreted as a signal of workers' preference for short hours. They do not, on the face of it, seem implausible: a reduction from 40 to 15 hours (10hours) represents a 63% (75%) reduction in working time, while an increase to 50 hours (55 hours) is a 25% (38%) increase. Thus, the required earnings changes are roughly proportional to the hours changes. Looking at night shifts, our evidence suggest that this job characteristic is perceived by workers as a strong disamenity requiring a compensation of almost 70% of the monthly wage. This figure is in line with the 90% found by Manning (2003) using UK LFS data.

1.4 Deriving MWP from job satisfaction

We now illustrate the alternative methodology for calculating workers' MWP for non standard working arrangements. This methodology is an application to the labour market case of the income compensation, or satisfaction, approach, using a specific measures of subjective well-being (SWB) - job satisfaction in our case - as a proxy for utility. As we show, MWP can then be identified from a job satisfaction equation including earnings and non-monetary characteristics.

This methodology has been increasingly applied by many authors in different fields, ranging from health, environmental, to labour economics. Ferrer-i-Carbonell and Van Praag (2002) use SWB data for Germany to estimate income compensations for chronic diseases. Ferreira and Moro (2010), Luechinger (2009), Luechinger and Raschky (2009), Frey et al. (2010) use the same methodology to value environmental attributes. Ferrer-i-Carbonell and van den Berg (2007) provide a monetary evaluation of informal care in Holland using SWB data. Clark and Oswald (2002), and Oswald and Powdthavee (2007) calculate income compensations for a variety of life events, like partner loss or divorce in, respectively, the US and the UK. Blanchflower and Oswald (2004), after investigating well-being trends in the UK and the US, use SWB data to estimate the average compensation for unemployment. Di Tella et al. (2001) use a similar methodology to calculate the trade-offs between macro-level unemployment and inflation using life satisfaction data. Stutzer and Frey (2008), and Dickerson et al. (2012) calculate willingness to pay for commuting time using SWB data for, respectively, Germany and the UK. Helliwell and Huang (2010) use data data on job satisfaction to value non-financial job characteristics.

1.4.1 Theoretical framework

In standard modern microeconomic theory, observed choices are sufficient to reveal preferences defined in terms of some underlying but unobserved utility function. But in recent decades, spurred by the increased availability of subjective measure of well-being and advances in psychological research, economists have started to re-consider a more direct approach to measuring welfare which dates back to the hedonic notion of utility advanced by Bentham [5]. In their influential contribution, Frey and Stutzer (2002) state the following:

> *The insights gained from research on happiness throw new light on important issues analyzed in economics. Most important, they enlarge the scope of empirical measurement and provide new tests for theories. Happiness is not identical to the traditional concept of utility in economics. It is, however, closely related. On the one hand, the concept of subjective happiness is a valuable complementary approach, which covers many more aspects of human well-being than the standard concept of utility. On the other hand, subjective well-being can be considered a useful approximation to utility, which economists have avoided measuring explicitly.*

Following this approach the monetary value of a good is the amount of income required to hold SWB constant following one-unit change in the amount of the good consumed. To the extent that SWB measures approximate utility, income compensations and marginal willingness to pay coincide, thus to apply this methodology we first need to identify a relevant measure of SWB to proxy utility from the job. Overall job satisfaction is the ideal candidate for the task given that its connections with workers' behaviour on the labour market have been widely documented in the literature.

If individual utility from the job depends on the wage and a set of non-wage job attributes, and job satisfaction is a proxy for utility, the MWP for our job characteristics of interest can be calculated as the monthly earnings increase (decrease) which is required to compensate changes in the relevant job attribute in order to hold job satisfaction fixed.

We assume that:

[5] For a general survey of the new economics of happiness literature refer to: Frey and Stutzer (2010); Van Praag and Ferrer-i Carbonell (2008)

$$JS(w,X) = f(u(w,X)) \tag{1.14}$$

where $f(\cdot)$ is a continuous, differentiable function.

From equation (1.14) it follows:

$$\frac{\partial JS(w,X)/\partial x}{\partial JS(w,X)/\partial w} = \frac{\dfrac{\partial f(u(w,X))}{\partial u(w,X)} \dfrac{\partial u(w,X)}{\partial x}}{\dfrac{\partial f(u(w,X))}{\partial u(w,X)} \dfrac{\partial u(w,X)}{\partial w}} = \frac{\dfrac{\partial u(w,X)}{\partial x}}{\dfrac{\partial u(w,X)}{\partial w}} \tag{1.15}$$

According to the above formula, MWP for the generic job attribute x is the ratio between marginal effects of x and w on job satisfaction. Note that MWP can be identified under weaker conditions than marginal satisfaction (utility) because MWP is the ratio of two marginal utilities, and they differ from "marginal job satisfaction" by the same constant of proportionality.

1.4.2 Estimation issues

Under the above identification assumption 1.14, all we have to do in order to calculate workers' MWP, is to estimate a standard equation for job satisfaction, and then calculate the marginal effects of the wage and non-wage characteristics. As described in Ferrer-i-Carbonell and Frijters (2004), we need to address two practical estimation issues.

On the one hand, It is well established in the literature that SWB measures are very sensitive to personality traits (e.g. the individual tendency to report high or low level of satisfaction). This would generate an omitted variable bias in our SWB equation if these personality traits are correlated with job attributes. The use of fixed effects should reduce this bias to the extent the latter are time-invariant.

On the other hand we need to take into account interpersonal comparability of individual SWB evaluations. Our ideal estimation framework should contain two key "ingredients":

a latent variable model accounting for ordinal comparability, and individual fixed effects to control for the potential endogeneity bias. This can written as:

$$JS_{it}^* = \alpha + \beta_{lnw} w_{it} + \beta_x' X_{it} + \gamma' Z_{it} + \nu_i + \varepsilon_{it}$$
$$JS_{it} = k \quad \text{if} \quad \lambda_k \leq JS_{it}^* < \lambda_{k+1} \tag{1.16}$$

While there is general agreement in the literature about the crucial importance of unobserved confounders when dealing with data on satisfaction, the potential consequences of using OLS (rather than ordinal methods) to model SWB indicators are not clear cut. In light of this ongoing discussion we decided to estimate our parameters of interest with three different estimators: a naive ordered logit model with no FE, a linear FE model, and the BUC estimator for FE ordered logit models developed by Baetschmann et al. (2015). While we present as main results the ones obtained using the linear approximation, the results obtained using the pooled ordered logit and the BUC estimator are presented in the appendix.

1.4.3 Estimates of MWP from job satisfaction equation

Tables 1.5 and 1.6 present, respectively, the estimated coefficients of the satisfaction equation estimated using a linear model with fixed effects. The estimated coefficients are then used to compute MWP according to equation 1.15. A similar argument to the one in section 1.3.3 can be used to go from equation 1.15 to 1.13, substituting $h(\cdot)$ with $JS(\cdot)$

Table 1.5: Job satisfaction, fixed effects OLS: estimated coefficients

	Waves 1-18		**Waves 9-18**	
	(1)	**(2)**	**(3)**	**(4)**
Real monthly earnings (log)	0.101***	0.169***	0.160***	0.190***
	[0.028]	[0.033]	[0.047]	[0.052]
Hours: 1-15	0.276***	0.350***	0.220**	0.258**
	[0.062]	[0.065]	[0.099]	[0.101]
Hours: 16-30	0.157***	0.194***	0.154***	0.158***
	[0.038]	[0.039]	[0.057]	[0.056]
Hours: 49 +	-0.037	-0.045	-0.058	-0.060
	[0.028]	[0.028]	[0.041]	[0.041]
Work at Night	-0.079**	-0.070**	-0.091*	-0.088*
	[0.036]	[0.036]	[0.051]	[0.051]
Rotating Shifts	-0.111**	-0.115**	-0.236***	-0.224***
	[0.048]	[0.049]	[0.073]	[0.074]
Flexitime			0.070*	0.053
			[0.039]	[0.038]
Other Flexible			-0.078*	-0.096**
			[0.043]	[0.045]
Additional Controls	yes	no	yes	no
Observations	33,959	33,959	16,092	16,092
Number of individuals	5,130	5,130	3,384	3,384

Notes: Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Additional controls included in all equations: gender dummy; age; age squared; family status dummies (3); dependent children dummy; education dummies (2); firm size dummies (3); union at the workplace dummy; region dummies (17); industry dummies (8) occupation dummies (6). The full set of results is provided in Appendix 1

The structure of table 1.5 follows table 1.3 . Results in the first two columns use data from all waves of the BHPS, while the last 9 waves are used to derive results in last two columns. In column 1 and 3 overall job satisfaction is modelled as a function of our key job characteristics only, while the same set of covariates used in the previous duration analysis is included in column 2 and 4

Estimated coefficients and implied MWP obtained using alternative estimators are presented in the appendix. Almost all the key job characteristics are significantly associated with job satisfaction in column 1 and these associations are strengthened by the inclusion of the full set of controls in column 2. Real monthly earnings, together with the two dummies for short weekly hours have a positive effect on overall job satisfaction, suggesting a "satisfaction premium" for part-time work. In contrast, a negative effect is found for night and rotating shifts. The effect of long hours is negative, as expected, although not statistically significant. Our evidence suggests a positive although not significant effect of flexitime and a negative and significant effect for other flexible arrangements. We also find the well documented U-shaped effect of age on our subjective measure of well-being, and lower levels of job satisfaction for never-married workers (the effects of other characteristics are not significant).

Table 1.6 presents estimated MWP for each of the job characteristics of interest, interpreted as the percentage of monthly earnings that a worker is willing to trade off for each job characteristic considered, in order to hold job satisfaction (and by assumption utility) fixed.

Table 1.6: MWP estimates using job satisfaction, fixed effects OLS

	MWP (%)	**S.E.**
Hours: 1-15	-0.873***	0.051
Hours: 16-30	-0.681***	0.080
Hours: 49+	0.302	0.217
Work at Night	0.512	0.340
Rotating Shifts	0.975	0.600
Flexitime	-0.243	0.162
Other Flexible	0.658	[0.467

Notes: *** p<0.01, ** p<0.05, * p<0.1. MWP's are expressed as fraction of real mothly earnings. MWP's for each characteristic are obtained using coefficients from table 1.5, column 2. MWP's for Flexitime and Other Flexible are obtained using coefficients from the same table, column 4. Standard Errors are obtained using Delta Method

The strong "satisfaction premium" for short hours translates in our context in very high estimated MWP. According to our estimates "traditional" full time workers are willing to take a monthly earnings cut of roughly 87% and 69% when moving to a job characterized by, respectively, less than 15 hours and 16-30 hours per week. Compared to the results obtained using job-to-job transitions, the estimated MWP are almost twice as large. We interpret the high statistical significance on the one hand, and the implausible magnitude on the other, as the signal of some possible misinterpretation of the underlying methodology which we discuss below. Among the remaining MWP for job attributes of interest, none of them is statistically significant at conventional levels.

In order to explore the potential consequences stemming from linearization of the outcome - implicit in our FE linear model for job satisfaction - we estimated the same model using the BUC estimator proposed by Baetschmann et al. (2015). The results are presented in the appendix, together with those obtained using a naïve pooled ordered logit which neglects unobserved heterogeneity. Looking at the implied MWP, we found almost no difference between the results presented above and the ones obtained using the BUC estimator, suggesting that linearizing an intrinsically ordinal outcome when the focus is on ratio between coefficients provides a good approximation. On the other hand, a comparison between estimated MWP with and without fixed effects, confirms, the crucial importance of individual unobserved heterogeneity when dealing with subjective measures of well-being, as argued by Ferrer-i-Carbonell and Frijters (2004).

1.5 A comparison and some possible interpretations

How do the the two sets of estimated MWP compare? The signs of the MWP estimates coincide for all the job characteristics of interest (except flexitime which is not significant) but there are considerable differences in significance and magnitude. Looking at statistical significance MWP for short hours are highly significant using the job satisfaction approach, while MWP implied by the duration model coefficients are not, with the exception of the MWP for 1-15 weekly hours. The same applies for the estimated MWP for night shifts which is significant only in the duration estimates.

Do the differences in magnitude form systematic patterns? The job satisfaction approach seems to amplify the effect of short hours. Using job delivers MWP lower magnitude, although not significant or slightly significant, implying a more realistic pay penalty. One may be tempted to argue, then, that the satisfaction approach tends to overestimate coefficients on non-monetary characteristics relative to the money measure, resulting in overestimated MWP (Benjamin et al., 2012). This pattern, however, is not clear-cut. Indeed, our estimated MWP for long hours derived using job satisfaction is relatively low in magnitude compared to its duration counterpart, and the same holds true for night shifts.

The differences and similarities just outlined give reason to think that the estimated quantities using the two approaches are linked but implicitly different. What emerges from the comparison is a potential difference between the theoretical "object" we would like to estimate and its empirical counterpart. Drawing on recent advances in the literature that distinguish between decision and experienced utility (Kahneman et al., 1997), we now link together the three main "ingredients" of our measures of MWP: job mobility, utility, and job satisfaction.

1.5.1 Some possible interpretations

On the one hand the duration approach is based on a on-the-job search model. Workers change their job when facing a new job offer only if the expected value of the new job is higher than the one of the current job. If workers choose those jobs which deliver the highest level of utility among the available options, job-to-job transitions should reveal impact of job characteristics on workers' utility. The concept of utility used here is decision utility, defined as the weight attributed to a given outcome in making a decision(Kahneman et al., 1997).

On the other hand the satisfaction approach is based on a measure of experienced utility, which is the actual wellbeing (in our case job satisfaction) associated with a given outcome (Chetty, 2015). There is an ongoing and recently expanding debate in behavioural economics about the extent to which experienced and decision utility coincide (Chetty, 2015). In a related study to ours, Akay et al. (2015) compare the income-leisure preferences revealed by labour supply choices (based on static labour supply models) with preferences implied by SWB equations. They conclude that preferences coincide on average, although they differ among some sub-populations who may be subject to choice constraints or optimisation errors. In the case of job search there appears to be considerable evidence that job satisfaction is a good predictor of quitting behaviour (see among others Hamermesh, 1977; Freeman, 1978; Clark, 2001; Lévy-Garboua et al., 2007; Green, 2010). If workers choose those jobs which deliver the highest level of (decision) utility among the available options, and job satisfaction is a good predictor of such choices, then utility and job satisfaction would appear to be closely linked. This represents a natural extension, to the job domain, of the theoretical approach adopted by the subjective well-being literature, which implicitly assumes that people make choices to maximise to SWB and that they are well informed about the consequences of their choices in terms of SWB (Benjamin et al., 2012). Job satisfaction can then be used as a proxy for utility and we can write

$$JS = g\left(U\left(w,X\right)\right) \tag{1.17}$$

where, following our previous notation, w and X represent, respectively, wage and non wage characteristics of the job and $g\left(\cdot\right)$ is a continuous, differentiable function. Differentiating both $JS\left(w,X\right)$ with respect to w and the generic element x within the vector X we get:

$$\begin{aligned} JS_x &= g_U U_x \\ JS_w &= g_U U_w \end{aligned} \tag{1.18}$$

From which:

$$\frac{U_x}{U_w} = \frac{JS_x}{JS_w} \tag{1.19}$$

Looking at quits:

$$h(w,X) = f\left(U\left(w,X\right)\right) \tag{1.20}$$

From which:

$$
\begin{aligned}
h_x &= f_U U_x \\
h_w &= f_U U_w
\end{aligned}
\tag{1.21}
$$

It would then follow:

$$
\frac{U_x}{U_w} = \frac{h_x}{h_w} = \frac{JS_x}{JS_w} \tag{1.22}
$$

From equation (1.22) it follows that the two methodologies should be able to estimate, in theory, the same empirical quantity of interest. Our empirical analysis, however, suggests that this is not the case using our data.

The second possibility we consider is that utility and SWB are distinct concepts. Workers make choices which are assumed to maximize utility but do not necessarily lead to the highest level of SWB. In this interpretation workers trade off SWB against other things they care about. Benjamin et al. (2012) provide experimental evidence that when alternatives differ in terms of money, subjects make choices that conflict with their SWB rankings of outcomes. Glaeser et al. (2014) find that people move to cities where they will be less happy but enjoy higher earnings or lower housing costs, and Adler et al. (2015) find that considerable numbers of people prefer health to happiness. In this view, SWB can be regarded as an argument in the utility function rather than a proxy for it.

For instance, it may be that job characteristics have both a direct impact on utility, and an indirect impact mediated by job satisfaction. Worker's utility could be re-written as:

$$
U\left(w, X, JS\left(w, X\right)\right) \tag{1.23}
$$

This is similar to the general theoretical formulation of Benjamin et al. (2012):

$$
U\left(X, H\left(X\right)\right) \tag{1.24}
$$

with $H(X)$ being SWB. The authors claim that, if people seek to maximize SWB alone the vector of partial derivatives U_X will equal zero. Using data on hypothetical choice and SWB indicator, they show that in the equation $\Delta U_{is} = \beta_H \Delta H_{is} + \beta_X \Delta X_{is} + \varepsilon_{is}$, the null hypothesis $H_0 : \beta_X = 0$ can be easily rejected. They use this as a test of the hypothesis that SWB is an important argument of the utility function rather than being its representation.[6] Translating this argument to the case of job satisfaction amounts to re-writing equation (1.20) as:

$$h(w,X) = f\left(U\left(w,X,JS\left(w,X\right)\right)\right) \tag{1.25}$$

If equation (1.25) embodies the true relation between job satisfaction and utility, rather than equation (1.20), then the ratio $\frac{h_x}{h_w}$ is no longer equal to $\frac{U_x}{U_w}$.

$$\begin{aligned} h_w &= f_U U_w + f_U U_{JS} JS_w \\ &= f_U \left(U_w + U_{JS} JS_w\right) \end{aligned} \tag{1.26}$$

$$\begin{aligned} h_x &= f_U U_x + f_U U_{JS} JS_x \\ &= f_U \left(U_x + U_{JS} JS_x\right) \end{aligned} \tag{1.27}$$

[6]Focusing on job satisfaction, Clark (2001) provides a theoretical justification for the inclusion of job satisfaction measures inside an equation representing voluntary separations which seems in line, at least implicitly, withBenjamin et al. (2012). Using his notation, V_i is the value function describing the utility stream in job i. An individual will quit to job j if $V_j - C > V_i$, with C being a moving cost. He argues that what's inside V_i is not just the wage rate, but a set of characteristics, so that $V_i = V(w_i, h_i, Z_i)$, with w_i representing the wage, h_i the number of hours worked, and Z_i a set of job characteristics. Interestingly, he suggests to use job satisfaction as a measure of "job quality" or "utility at work" within the Z vector of non monetary characteristics. This implicitly defines job satisfaction an element of the utility function, a measure of quality of the job match on the side of the worker, which can be traded off for something else that workers care about.

Looking at the ratio

$$
\begin{aligned}
\frac{h_x}{h_w} &= \frac{f_U\left(U_x + U_{JS}JS_x\right)}{f_U\left(U_w + U_{JS}JS_w\right)} \\
&= \frac{U_x + U_{JS}JS_x}{U_w + U_{JS}JS_w}
\end{aligned}
\tag{1.28}
$$

If we believe this interpretation of job satisfaction, and the consequent representation of the rate for voluntary separations in equation (1.25), the last equation implies the estimated MWP we presented in table 2 need not to coincide with the marginal rate of substitution , $\frac{U_x}{U_w}$, given we are not controlling for job satisfaction in that case.

Our empirical framework is different from the one in Benjamin et al. (2012) in that we structurally interpret ratios of coefficients of a duration model for job quits rather than focusing on the impact of a set of explanatory variables in a random utility model for choices. However, in the same spirit, we can verify whether the inclusion of job satisfaction in our duration model changes the effect of our job characteristics of interest. Under the hypothesis that the unique driver of workers' voluntary separations is job satisfaction, we would expect no explanatory power for job characteristics once job satisfaction is controlled for. In contrast, if non monetary characteristics have both a direct impact on utility and an indirect one mediated by job satisfaction, we would expect that the ones which are significant in our specification for the hazard ratio of separation stay significant even after the inclusion of job satisfaction. Our results are presented in table 1.7.

As expected, our findings confirm that job satisfaction is a good predictor of voluntary quits. Its coefficient in our duration model is negative and highly statistically significant, confirming the previously mentioned findings in the literature: people who are less satisfied of their jobs are more likely to quit. Second, focusing on our job characteristics of interest we find that controlling for overall job satisfaction slightly changes the magnitude of coefficients in the direction predicted by our satisfaction equation. Comparing the estimated coefficients in table 1.3 and table 1.3, however, we find that those characteristics which were significant before the inclusion of job satisfaction - monthly earnings, long hours, and night shifts - are still significant when job satisfaction is added to the model specification. Our evidence seems to suggests that the interpretation of job satisfaction as an element of the utility function is preferable to the one under which it can be used as a proxy for it. We regard this evidence as a further confirmation of the difference between (decision) utility and subjective well-being.

Table 1.7: Duration model for job-to-job transitions adding job satisfaction: estimated coefficients

	Waves 1-18	**Waves 9-18**
	(1)	**(2)**
Real monthly earnings (log)	-0.312***	-0.164*
	[0.058]	[0.088]
Hours: 1-15	-0.092	0.079
	[0.134]	[0.210]
Hours: 16-30	-0.042	0.080
	[0.082]	[0.119]
Hours: 49 +	0.113*	0.149
	[0.062]	[0.095]
Work at Night	0.155**	0.099
	[0.071]	[0.102]
Rotating Shifts	0.075	-0.006
	[0.087]	[0.154]
Flexitime		0.070
		[0.099]
Other Flexible		0.058
		[0.161]
Job Satisfaction: Overall	-0.227***	-0.242***
	[0.014]	[0.022]
Additional Controls	yes	yes
Observations	33,959	16,092
Number of individuals	5,130	3,384
Number of spells	12,330	6,184

Notes: Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1; Additional controls included in all equations: gender dummy; age, age squared, family status dummies (3), dependent children dummy, education dummies (2), firm size dummies (3), union at the workplace dummy, region dummies (17), industry dummies (8), occupation dummies (6); wave dummies (17). The full set of results is provided in the appendix.

1.6 Conclusions

The objective of this paper was to estimate and compare MWP for some job characteristics using two different approaches. Our evidence suggests that estimates obtained differ across the two methodologies. Drawing on the recent expanding literature on decision and experience utility, we presented a potential theoretical explanation of the possible differences building on alternative interpretations of job satisfaction

We try to assess whether job satisfaction can be interpreted as a measure of job quality on the workers' side - hence an element of the utility function - rather than a proxy for utility as suggested by the economics of happiness literature. In order to so we include job satisfaction in our duration model for quits, and test the hypothesis that those coefficients of our relevant job characteristics which were significant before the inclusion of job satisfaction are still significant when we control for it. Our results show that some of our job characteristics of interest are likely to have both a direct and indirect effect on the hazard rate of separation. Under a structural interpretation of the duration model, this evidence would suggest that job satisfaction stands as element of the utility function rather than its representation.

Even if we cast legitimate doubts about a structural interpretation of the duration model due to its necessary simplistic assumptions, the relationship we estimate between job-to-job transitions and our job characteristics of interest do exist in the data. On the one hand our results suggest that some job characteristics affect job-to-job transitions. On the other hand the same characteristics have an impact on job satisfaction. Though job satisfaction is confirmed to be a good predictor of voluntary job mobility, job characteristics are still important in an equation for quits even when controlling for it. Job satisfaction seems not to be the object that people seek to maximize when facing an alternative job offers. It helps explaining quits, but it is not the only driver of job mobility. It is then better regarded as one among several elements of the utility function. Job satisfaction, as well as any measure of subjective well-being, refers to an experience. Borrowing Bentham's words it refers to the feelings coming from the experience of a job. It is then likely that for a number of reasons, well explained by Khaneman among others, what people actually choose is not what delivers them the highest amount of pleasure. As a consequence, even in the lucky case in which we are able to perfectly identify choices, they need not to coincide with what people actually prefer from a hedonic perspective. This is to say that utility and well-being are intrinsically connected concepts, but not the same "thing".

Our results raise obvious questions about which measures of MWP should be preferred (MWP in terms of decision utility or well-being?) as well as the implications for welfare measurement and policy. Views differ on whether welfare should be assessed in terms of decision or experience utility. Both Chetty (2015) and Glaeser et al. (2014) consider situations of residential mobility but come to opposite conclusions about the use of SWB measures. Chetty focuses on cases in which families fail to take full account of their own (and their children's) experience utility when deciding where to live. Optimal policy may then be to use tools such as housing vouchers to nudge them into decisions that increase their SWB. On the other hand Glaeser et al. (2014) argue that people knowingly choose less SWB for more income and thus SWB is a poor measure of overall welfare, and relying on it can lead to welfare-reducing policies. Similar considerations may apply to our divergent measures of MWP of working hours or night shifts. Should they be valued by what workers choose (knowingly?) or what makes them happy?

One thing appears certain: while economists model individual preferences are the main drivers of choices, and regard utility an important theoretical construct which represents them, we should give up the possibility of measuring it through SWB indicators. In light of this, our estimated MWP will then remain what they actually are: a measure of trade off between money and non-monetary characteristics in terms of job satisfaction. More importantly, claiming that satisfaction is a proxy for utility becomes irrelevant once we accept, as economists, the idea that subjective well-being indicators are welfare measure per se. Job satisfaction describes one aspect of workers' well-being which can be used, to some extent, to predict part of workers' behaviour, but does not need to coincide with the economists' notion of utility.

Chapter 2

Measuring the long-run effects of temporary work using observed consumption and saving choices

Introduction

Temporary jobs are generally regarded as undesirable jobs. They tend to be associated with low levels of work-specific training and bad working conditions in terms of wage, insecurity, and schedules (Segal and Sullivan, 1997; Booth et al., 2002; Kahn, 2007). These characteristics might negatively affect workers' accumulation of firm-specific human capital, and motivation, resulting into poor career prospects. Another major detrimental consequence for workers' welfare is related to the level of employment stability associated to temporary work, which is likely to reinforce the mechanism leading to low-pay traps and precariousness. Supporting evidence shows that, after the termination of a temporary job, individuals are likely to find a new temporary job or to become unemployed, especially if the temporary work spell comes after an episode of unemployment (Boheim and Taylor, 2002; D'Addio and Rosholm, 2005; Gagliarducci, 2005; Guell and Petrongolo, 2007; Arranz et al., 2010).

In contrast, some authors have provided evidence suggesting that temporary employment can be better regarded as part of a transition towards better and stable jobs. Temporary jobs might help unemployed individuals to gain some work experience and maintain or acquire human capital, providing contacts with potential employers, thus serving as stepping stones towards better and stable jobs, or an opportunity to re-gain employment after displacement. Several contributions in the applied literature have tested the stepping stone hypothesis, but the evidence remains mixed. In the US Addison and Surfield (2009) document a stepping stone effect of temporary work, while Autor and Houseman (2010) find that temporary-help jobs do not improve subsequent earnings and employment outcomes. Concerning Europe,Booth et al. (2002), Hagen (2003) provide evidence in favour of the stepping stone hypothesis for, respectively, UK, and Germany, while weaker evidence is found for the Netherlands in de Graaf-Zijl et al. (2011). Blanchard and Landier (2002) conclude that the excess turnover induced by the increase of temporary jobs had negative consequences for the welfare of young workers in France. Similarly, Amuedo-Dorantes (2000) supports the view of temporary work as a trap for Spanish workers rather than a stepping stone owing to the detrimental effects of contractual persistence also observed by Arranz et al. (2010) for Spain and Gagliarducci (2005) for Italy. Berton et al. (2011) document the coexistence of both a stepping stone and a scarring effect of temporary work in Italy, with the former depending on the specific type of contract and tenure with the firm.

The most common approach used in the applied literature to investigate the consequences of temporary work for future employment outcomes has revolved around estimation of various models for the conditional probability or the duration up to transitions to different states, most commonly identified as a new temporary job, unemployment, and a permanent job. While observing workers' trajectories may provide a good ex-post measure of how temporary work affects labour market transitions, it explicitly requires a long observational period, and, more importantly, is not informative about how workers perceive the consequences of temporary work for their welfare.

The objective of this paper is to tackle the issue from a different perspective, one that specifically focuses on how workers' internalize the potential welfare costs and (or) opportunities associated to temporary work. I propose a different empirical framework in which consumption and saving choices are used as measures of future prospects. A similar approach has been recently used by Browning and Crossley (2008) to investigate the long-run costs of job loss. Given the difficulties in mapping observable short-run changes in earnings after displacement into long-run welfare costs, the authors suggest a viable alternative based on the idea that consumption changes should reflect agents' expectations of the long-run effects of displacement, and their willingness to self-insure against the shock. In a similar manner, changes in consumption and saving patterns are used in this paper to understand whether workers expect temporary work to be a stepping stone towards better jobs, or a source of uncertainty and insecurity.

According to the permanent income hypothesis, individuals who expect their earnings to permanently increase in the future, should adjust their optimal path by increasing consumption, or, equivalently, decreasing saving. This is likely be the case if temporary jobs are held by young individuals, and, more importantly, if a stepping stone effect towards better and stable jobs exists and is perceived by individuals. However, the process that leads to more desirable jobs can be far from smooth, and workers in temporary jobs might not be able to perfectly foresee if their contract will be extended, converted, and if not, when they will re-gain employment, inducing some degree uncertainty.

When individuals face income uncertainty, and have preferences characterized by prudence, the precautionary motive provides an additional reason for saving other than expected declines in income. As a consequence, individuals who are subject to higher uncertainty lower consumption and accumulate savings in order to mitigate the consequences of potential future losses. Among the sources of earnings uncertainty, the probability of being unemployed in undoubtedly one of the most important, and has been used as measure of earnings risk in different empirical studies (i.e. Carroll et al., 2003). If temporary work is associated with low employment continuity and workers in temporary jobs perceive a greater unemployment risk, they should, in principle, self-insure against the perceived risk by postponing consumption and saving more.

Using data from all the eighteen waves of the British Household Panel Survey (BHPS hereafter), I first document how temporary work relates to earnings, earnings growth, residual earnings variability, and unemployment risk for household heads. Compared to permanent employment, temporary work entails an income penalty, but also with higher income growth in the short run. A simple test based on subjective expectations also suggests that household heads correctly predict, on average, growth in future earnings.On the other hand, temporary work increases the likelihood of future spells of unemployment, and entails a higher variability of residual earnings growth, both of which are used as measures of uncertainty.

In order to assess which of these two effects dominates, I estimate the reduced forms of consumption and saving functions.

Once transitory income is accounted for, temporary work for the household head has no significant effects on average household's monthly saving and consumption. The evidence provided indicates that, faced with a temporarily low income, households whose head is currently employed in a temporary job, smooth consumption in anticipation of higher future earnings, consistently with the permanent income hypothesis. Moreover, the lack of a significant positive (negative) effect on saving (consumption), suggests that the increased uncertainty associated to temporary work with respect to permanent employment, does not result in a stronger precautionary motive for saving.

Everything considered, the results provided in the paper suggest that a stepping stone effect towards better jobs is present and, more importantly, is perceived by individuals and internalized in their behaviour.

One potential source of endogeneity bias that can affect the results is due to the fact that individuals might, in principle, self-select into temporary jobs. As suggested by Lusardi (1997) and Fuchs-Schündeln and Schündeln (2005), workers less averse to risk are more prone to end up in jobs with higher risk of unemployment and higher earnings variability. In order to mitigate the potential endogeneity bias I exploit the panel dimension of the data by allowing unobserved heterogeneity in all the estimated equations. If self-selection is driven by characteristics like risk aversion, not fully accounted for by the set of covariates, allowing for unobserved heterogeneity helps mitigate the problem to the extent that these characteristics are time-invariant. Moreover, fixed effects should be able to account, at least partially, for differences in life-time earnings in estimates of saving and consumption functions.

To the best of my knowledge, Barcelo' and Villanueva (2010) is the only previous contribution in the literature that looks at the relationship between temporary work and consumption and saving. Although the work by the two authors is aimed at a different task, and the analysis is based on cross-sectional data, (testing the existence of a precautionary motive for saving in Spain using temporary work as a proxy for the risk of job loss), their results are intrinsically related to the analysis in this paper. The evidence by the two authors indicates the existence of precautionary savings for households whose head is in a temporary job: the average stock of liquid wealth for households headed by male fixed-term workers exceeds by 30% the one held by households with same characteristics except for the contract type of the household's head (open-ended). These findings, in the lights of the ones in this paper, are suggestive of the intrinsic differences between the Spanish and British labour market. Contrary to the UK, Spain is, indeed, one of the European countries where the share of workers in temporary jobs grew the most during the 90s and 2000s, and where temporary work has been constantly documented as a dead end in the literature.

The chapter is organized as follows. Section 2.1 reviews the literature on temporary work in Britain. Section 2.2 provides a simple theoretical framework for consumption and saving under uncertainty. The data used are described in section 2.3. Section 2.4 illustrates how temporary work relates to earnings, earnings growth and expectation, unemployment risk and earnings variability. Estimates of the reduced forms for saving and consumption functions are presented in section 2.5. Section 2.6 concludes.

2.1 Temporary work in Britain

In the past twenty years Britain has been one of the OECD countries with the least strict employment protection legislation. This helps to explain why the share of employees covered by temporary contracts has been quite small during the 90s and 2000s, especially if compared with countries where two-tier reforms have been put in place to overcome labour market rigidities (e.g. Italy, Spain, France) (Booth et al. 2002).

The analysis of Booth et al. (2002) focuses on the effect of temporary work for British workers covering part of the time span under analysis in this paper. Using data from the first seven waves of the British Household Panel Survey (1991-1997), the authors document negative effects of temporary employment on job satisfaction, work-related training and wages. However, the authors show that these costs are mainly transitory, suggesting a stepping stone effect at least for fixed-term workers. The median male (female) fixed-term worker transit to a stable job in 3 years (3 and a half years), with wages that partially (men) or fully (women) catch up with those of individuals starting their careers in standard employment. Seasonal workers, in contrast, face a low probability of moving to permanent contracts.

However, notwithstanding the improving conditions of the British labour market in the period considered in Booth et al. (2002), some evidence shows that temporary workers are more likely to experience unemployment spells, and to exhibit feelings of job insecurity. Boheim and Taylor (2002) use BHPS data from 1991 to 1997 to analyse how unemployment experience affects individuals' future career. They show that job spells started after involuntary separations like the end of a temporary contract are more likely to terminate with another involuntary separation or exit to unemployment. In a companion paper,Boheim and Taylor (2000), using the same data, document that among men (women) 53% (56%) of temporary jobs exits are followed by employment, while 39% (28%) by unemployment, and 8% (16%) by inactivity. The fraction of temporary jobs ending in unemployment raises to 45% (48%) when focusing on jobs started after unemployment.

Turning to subjective measures, Green and Heywood (2011) find that temporary jobs have strong negative effects on satisfaction with job security. Similar results can be found in Dawson and Veliziotis (2013). Green et al. (2000) using data from the Social Change and Economic Life Initiative (1986) and Skills Survey (1997) documents a strong positive association between temporary jobs and perceived job insecurity in all occupations.

2.2 Conceptual framework

The conventional theoretical framework used to analyse consumption and saving choices is the life-cycle model developed by Modgliani (1954) and Friedman (1957). Since its original formulation, the model has been enriched by several modifications in order to relax part of its assumptions, and explain some "consumption puzzles". Allowing for uncertainty and prudence is one of the most important among these modifications.

When income is uncertain and agents' preferences exhibit prudence, consumption and saving respond not only to expected changes in income, as predicted by the permanent income hypothesis, but also to the degree of uncertainty. This creates an extra reason for saving which is referred to as the precautionary motive (Leland 1968 and Sandmo 1970).[1]. All these characteristics can be illustrated using a very simple, yet intuitive, model based on Caballero (1990) and Weil (1993).

In this model, an infinitely living agent chooses the optimal consumption path to maximize the expected present discounted value of future utility. The utility function is assumed to

[1] Kimball (1990) defines prudence as "the propensity to prepare and forearm oneself in the face of uncertainty", in the context of consumption and saving it "represents the intensity of the precautionary motive". From an algebraic perspective the existence of a precautionary motive is associated with convexity of the marginal utility function, or, equivalently, the existence of a a positive third derivative, as shown by Leland (1968) and Sandmo (1970). Kimball (1990) provides a measure of absolute and relative prudence using the ratio between the third and and the second derivative of the utility function.

be exponential with constant absolute risk aversion (CARA) to allow for prudence, and to ensure a closed form solution for the consumption function. The maximization problem can written as:

$$\max_{c_t} \quad E_t \sum_{i=0}^{\infty} \beta^i \left(-\frac{1}{\theta}\right) \exp\left(-\theta c_{t+i}\right) \tag{2.1}$$

The income process is described by

$$y_t = \rho y_{t-1} + (1-\rho)\hat{y} + \varepsilon_t \tag{2.2}$$

The term $\hat{y}$ represents the deterministic component of income, and corresponds to its long-run average. The coefficient ρ governs the persistence of income shocks ε_t, which are further assumed to follow a $N\left(0,\sigma^2\right)$ distribution. ε is the only source of uncertainty in this setup. Under these assumptions, it can be shown that a closed form solution for the consumption function exists and can be written as:

$$c_t = \frac{R-1}{R-\rho}\left(y_t + \frac{1-\rho}{R-1}\hat{y} + w_t\right) - \frac{\theta\sigma^2}{R-\rho} \tag{2.3}$$

The RHS of the above equation is composed by two parts. The first component represents the amount of consumption under certainty equivalence, which is to say the level of consumption which would prevail in absence of uncertainty. The second part is what defines the precautionary motive for saving. The optimal consumption path depends negatively on the variance of the income process σ^2, on the coefficient of relative prudence θ characterizing the utility function, and the persistence of income shocks ρ.

Following Campbell (1987), and Wang (2003) it can be shown that, by imposing the budget constraint, the consumption function can be alternatively re-written in terms of saving as:

$$s_t = \frac{1-\rho}{R-\rho}(y_t - \hat{y}) + \frac{\theta\sigma^2}{R-\rho} \tag{2.4}$$

The second component of the RHS in this latter equation, already seen with opposite sign in the consumption function, tells us how saving react to uncertainty about future income. The first component reflects, instead, the agent's demand for savings due to expected change in income. This is the level of saving which would prevail in absence of uncertainty ($\sigma^2 = 0$). It shows how savings can be generated due to the difference between the current and the expected level of income, When $y_t > \hat{y}$, agents expect that their income will fall in the long run. This induce them to save a fraction of current income, which depends on the persistence of the income shocks ρ. The lower the persistence of the income process, the higher the marginal propensity to save out of current income. Conversely, when $y_t < \hat{y}$, agents expect that their income will raise, providing an incentive to borrow, or decrease their level of savings.

Although the assumptions made about the utility function and the income process are quite restrictive, the equations above convey an important intuition which will be of crucial importance when interpreting the results in future sections: expectations and uncertainty about future income have separate, and potentially opposite, effects on consumption and saving choices.

2.3 Data description

The empirical analysis in this paper is based on all the eighteen waves of the British Households Panel Survey (BHPS). The BHPS is a nationally representative longitudinal study run between 1991 and 2008. The information collected within the survey spans a variety of topics both at the household and individual level, including demographic, educational, job-related, income characteristics[2].

[2]Between 1991 and 2008 four extension samples have been added to the original 1991 sample: ECHP extension (waves 7-11), Welsh extension (waves 9-18), Scottish extension waves (waves 9-18), Northern Ireland extension (waves 11-18). By referring to the BHPS in this paper I refer to the full BHPS sample, including these extensions. Since longitudinal weights (accounting for differential non-response, including attrition) are available only for the original 1991 sample, all the regressions in this paper are unweighted. This might raise concerns about the potential bias induced by unequal sampling probabilities and non-response. As stated by Solon et al. (2015), regression estimates are biased if sampling and non-response are not independent of the dependent variable conditional on the explanatory variables. The inclusion of region and

Focusing on the measure of saving, individual respondents are asked at each wave, the following question regarding their saving behaviour: *"Do you save any amount of your income, for example by putting something away now and then in a bank, building society, or Post Office account other than to meet regular bills?“.* If the answer is positive, they are asked to report the average monthly amount.

Concerning consumption, respondents are asked to report the average weekly expenditures of the household for food and grocery. This information is recorded in twelve expenditure bands ranging from 1 (10£ per week), to 12 (more than 150£ per week)[3]. Additional information is also available at each wave concerning housing costs, either in the form of mortgage repayments or rent, and households' monthly expenditures on gas, oil and electricity. On top of that, two additional questions have been added to the questionnaire from wave 7 onwards about personal expenditures for leisure activities and outside meals. Similar to food and grocery expenditures, this information is also recorded in bands. Since consumption bands are quite "tiny" - roughly 10£ - the bands' mid points are used as an approximation in this paper. This is done to overcome the modelling difficulties connected to the discrete nature of the variable.

It is evident from this discussion that consumption and saving information contained in the BHPS provides a partial picture of how households allocate their resources. On the one hand, only average active savings are measured. On the other hand, consumption information is available only for sub-components of total expenditures. Finally, both measures are subject measurement error due to under-reporting and recall bias. Notwithstanding these limitations, these imperfect measures have been extensively used in the literature (cite examples). Moreover, since consumption and saving are in principle related through the budget constraint, estimation of both saving and consumption functions mitigates con-

wave dummies in all regression models should address the issue of unequal probabilities due to the extension samples. Non-response, instead, is not issue to the extent that, conditional on the set of covariates, data are missing completely at random.

[3] The only exception is wave one, in which households were required to put a precise figure in answer to this question.

cerns about how data reliability might affect the results, by providing a double test of the same hypotheses.

Although information about saving, and some of the dimensions of consumption is relative to individuals, saving decisions are likely to be taken at household level, as often argued in the literature. For this reason, I follow the the standard approach in the applied literature and consider the head of the household as the unit of observation.

As in previous literature, I restrict the sample to individuals who are constantly observed as household heads, and whose the partner, if present, remains the same (this is the definition of an "intact household" used, among others, by Carroll and Samwick 1997; Giavazzi and McMahon 2012, and Guariglia 2001). Consumption and saving of head and partner are aggregated accordingly. I further exclude household heads who are: i) younger than 20 or older than 65, ii) never observed in employment, iii) self-employed. The resulting sample consists of 22.992 obervation-years for 3.589 household heads.

The main variable of interest is this paper is an indicator variable for temporary work, which takes value 1 if the household head reports to be in a temporary job - either fixed-term or seasonal - at the time of interview, and zero otherwise. Table 2.1 summarizes the characteristics of the full sample, and of the sub-sample of heads who report to be in a temporary job at least once. While the fraction of heads in temporary jobs is equal to 3.5% of the sample, 22.4% of them report to be in a temporary job at least once during the observation period. For these individuals, the average (median) time spent in temporary work correspond to a fraction of 19% (12%) of the their total number of observations. Descriptive statistics in the table also suggest that this sub-sample of heads does not differ greatly from the the full sample for most of the considered characteristics.

The sample distribution of saving and consumption is summarized in table 2.2. All monetary values are deflated using RPI, and are expressed in 2008 GBP. 51% of the households report zero average monthly savings. The average (median) household's real monthly saving flow is roughly equal to £140 (£44), raising to £245 (£150) when focusing on households who report positive saving. The average (median) household saves 4.5% (1.8%) of total earnings, while the average (median) saving household saves 7.8% (5.7%) of earnings.

Household's expenditures for food and grocery are labelled CONS1 in table 2.2. CONS2 refers, instead, to the sum of expenditures for food and grocery, housing, oil/gas/electricity, leisure activities, and outside meals. Statistics for CONS2 are relative to waves 7-18 for which the relevant information is available. The average (median) household consumes £902£ (£837) in a month, of which £314 (£293) for food and grocery.

These figures compare quite well with diary-based data from the Expenditure and Food Survey (EFS). Between 2002 and 2008 (2002 is the year in which the Family Expenditure Survey was replaced by the Expenditure and Food Survey, and the COICOP classification of expenditures introduced), the average household's monthly expenditure for food and grocery was £326. Aggregating items of the COICOP classification comparable to the ones measured in the BHPS, the average expenditure - between 2002 and 2008 - for food and grocery, housing (including bills), leisure (recreation and culture), and restaurants, is equal £1017. This also suggests that the two variables CONS1 and CONS2 represent, approximatively, 12% and 46% of total expenditures.[4].

[4]EFS data used for these calculations are published by ONS in "Family Spending: 2015", and are publicly available for online consultation on ONS website.

Table 2.1: Characteristics of the sample of household heads

	Mean - Full Sample	Mean - Temp. Work		Mean - Full Sample	Mean - Temp. Work
Temporary work	0.035	0.224	N. of dependent children in HH		
Fraction of obs. period in temp.work	0.031	0.198	none	0.571	0.579
Female	0.281	.391	1	0.184	0.189
Age			2	0.181	0.166
<25	0.031	0.031	3+	0.064	0.066
25-34	0.202	0.185	N. of adults in HH		
35-44	0.312	0.301	1	0.247	0.276
45-54	0.289	0.297	2	0.543	0.517
55+	0.166	0.185	3+	0.210	0.207
Occupation:			N. of ind. in paid work in HH		
Large employers & higher management	0.059	0.029	none	0.025	0.055
Higher professional	0.079	0.074	1	0.388	0.405
Lower management & professional	0.269	0.232	2	0.483	0.446
Intermediate	0.123	0.136	3+	0.104	0.094
Lower supervisory & technical	0.145	0.124	Log real monthly earnings (Head)	7.290	6.952
Semi-routine	0.144	0.157	△ Log real monthly earnings (Head - 1 yr.)	0.025	0.038
Routine	0.136	0.152	△ Log real monthly earnings (Head - 2 yrs.)	0.039	0.051
Unemployed	0.023	0.049	Unemployed in the 12 months after interview	0.042	0.099
Inactive	0.023	0.045	Log real monthly earnings (HH)	7.621	7.383
Family status			Real monthly saving	150.401	122.645
Never married	0.168	0.204	Real monthly expenditures - CONS1	320.500	309.516
In union	0.692	0.644	Real monthly expenditures - CONS2	924.659	874.210
Separated	0.118	0.126			
Widowed	0.023	0.025			
Observations	22.992	3.631			
Units	3.589	501			

*Sample mean of CONS2 is relative to waves 7-18 (15,102 observations for 3.015 units)

Table 2.2: Sample distribution of household's saving and consumption

	Saving (£/month)		Consumption (£/month)	
Decile	Overall	If saving	CONS1	CONS2
1^{st}	0	38.613	140.016	448.274
2^{nd}	0	60.364	181.222	570.016
3^{rd}	0	92.163	221.263	668.707
4^{th}	5.431	120.729	265.531	764.486
5^{th}	55.725	155.266	304.389	861.555
6^{th}	104.782	217.256	337.949	963.691
7^{th}	156.031	278.627	392.045	1,082.212
8^{th}	252.213	378.319	442.527	1,233.837
9^{th}	430.448	574.388	531.063	1,468.618
Mean	150.401	250.399	320.499	924.659
S.D.	249.676	280.619	153.629	430.447

Notes: CONS1 - food and grocery expenditures; CONS2 - food and grocery expenditures, rent and mortgage repayments, oil/gas/electricity bills, and expenditures for leisure and outside meals; The distribution of CONS2 is relative to waves 7-18.

2.4 Earnings and uncertainty

The objective of the analysis in this section is to investigate how temporary work relates to earning and uncertainty by looking at the relationship between temporary work and earnings, earnings growth, residual earnings variability, and unemployment risk.

2.4.1 Temporary jobs and earnings

In the consumption literature, labour earnings are assumed to follow a stochastic process, which is, in turn, assumed to be known by individuals. Under these assumptions, estimates of the the income process can be used, in principle, to provide a measure of expected future earnings, as well as a proxy for the degree of uncertainty faced by individuals. In the model sketched in section 2.2, as an example, the deterministic component of the income process corresponds to its long-run average, and is the best guess that individuals can make about their future level of earnings. As a consequence, a first way to look at the relationship between temporary work and expectations would be to estimate an income process which explicitly accounts for temporary work. This would, however, require some specific assumptions about the true structure of the stochastic process.

In order maintain some degree of agnosticism about the latter, a simpler, but still informative, approach is adopted here. I first estimate the following regression to describe the evolution of labour earnings for each individual:

$$ln\,y_{it} = \beta_0 + \beta_{TW} TW_{it} + \beta_X X_{it} + d_t + c_i + u_{it} \tag{2.5}$$

where $ln\,y_{it}$ is the log of average monthly labour earnings, and is derived from the measure of individual annual labour income provided in the BHPS. The vector X_{it} contains a set of individual demographic and work related time-varying characteristics, d_t is a set of time dummies, and c_i represents individual unobserved heterogeneity. The main variable of interest is TW_{it}, the indicator variable for temporary work described in the previous section.

The equation is estimated via fixed-effect OLS. The use of fixed effects allows to account for time-constant unobservable determinants of earnings potentially known to individuals, and offers an interpretive advantage. By focusing on within-indvidual variations, the coefficient β_{TW} tell us how, on average, earnings during a temporary job compare with earnings during a permanent job for a given individual. The estimated β_{TW} in table 2.3 (column 1) is found statistically significant and equal to -0.3373, suggesting that temporary work entails a severe earnings penalty with respect to permanent employment, equal to roughly 38%.

Turning to income changes, the following regression is used to test whether whether temporary work is followed by earnings growth:

$$\Delta ln\,y_{t,t+j} = \delta_0 + \delta_{TW} TW_{it} + \delta_X X_{it} + d_t + c_i + \varepsilon_{it} \tag{2.6}$$

where $\Delta ln\,y_{t,t+j}$ is the change in log labour income between t and $t+j$ ($ln\,y_{t+j} - ln\,y_t$).

The regression is separately estimated for 1-year-ahead ($j = 1$), and 2-years-ahead ($j = 2$) variations.[5]

The conditioning set on the RHS of equation (2.6), like the one in equation (2.5), purposely contains only information about individual characteristics at time t. It represents a subset of the full information set available to agents, Ω^F_{it}, to form expectations about future changes in income. The earnings growth equation can, then, be interpreted as a representation of rational expectations in which time invariant unobserved heterogeneity complements the limited information set available to the econometrician, Ω^E_{it}, by capturing part of unobservable private information.

The estimated δ_{TW} for the case $j = 1$, and $j = 2$, are presented, respectively, in columns 2 and 3 of table 2.3. The results indicate that, on average, compared to permanent employment, temporary work is followed by a 11.2, and 13.8 percentage points higher earnings growth within, respectively, 1 year, and 2 years.

A natural question is whether the rational expectations argument is likely to hold, which is to say the extent to which realized changes in income correspond to what individuals expect. A partial answer to this question can be provided resorting to BHPS data on subjective expectations reports. Respondents of the BHPS are asked every year to report subjective expectations regarding their financial situation in the next year. The answers are coded into four categories; "don't know", "same as now", "better than now", and "worse than now". The ordinal indicator variable for expectations reports, ER_{it}, can be thought as the representation of a latent continuous variable measuring expectations about future changes in economic conditions.

I provide a simple test to check whether future income realizations are consistent with

[5]The use of a log specification for earnings might rise some concerns about the possibility of excluding individuals who are unemployed and potentially experienced a spell of temporary work. The use of the BHPS derived variable for annual earning mitigates the issue: even in the presence of an unemployment spell the amount of annual labour earnings does not need to be zero if the unemployment spell did not cover the entire year. In order to understand whether the issue is still likely to bias the results, the level equation has been estimated without logs, and the growth equations have been estimated using the simple difference ($\Delta y_{t,t+j}$), and a percentage difference which uses at the denominator the average between the begin and the end of the period level to avoid the zero problem ((($\Delta y_{t,t+j}$) / ($\bar{y}_{it,t+j}$)). The results are insensitive to such changes.

individuals' forecasts measured by their subjective expectations. The test is based on a simple OLS regression of future income growth - $\Delta ln y_{t,t+j}$ - on the ordinal indicator variable representing financial expectations ER_{it}. The results of this test are provided in table 2.3.

Reassuringly enough, the test shows that the coefficients of interest are statistically significant, and have the expected signs. Optimistic expectations are associated with positive earnings growth, while the opposite holds true for expected worsening of future financial conditions. Notwithstanding the limitations of subjective expectation reports (i.e. the phrasing of the expectations question only asks individuals to comment on how they will be 'financially' in a year's time and, hence, is relatively vague), the test confirms previous findings in Brown and Taylor (2006) about their forecasting accuracy, and mitigates potential concerns about the applicability of the rational expectations argument mentioned above.

Table 2.3: Temporary jobs and earnings

	Earnings	Earnings growth		Subjective expectations test
	$\ln(y_{it})$	$\Delta \ln y_{it,t+1}$	$\Delta \ln y_{it,t+2}$	$\Delta \ln y_{it,t+1}$
	FE OLS	FE OLS	FE OLS	FE OLS
	(1)	(2)	(3)	(4)
Temporary work	-0.3373***	0.1062***	0.1298***	
	[0.020]	[0.025]	[0.031]	
ER_{it} = "worse"				-0.0621***
				[0.014]
ER_{it} = "better"				0.0345***
				[0.010]
Additional controls	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes
Observations	22,992	17,812	14,883	17,812
Units	3,589	3,317	2,798	3,317

Notes: Robust standart errors in brackets; Column (1) dependent variable is the log of annual labour earnings. Columns (2)-(4) and (3)dependent variables are, respectively, the 1-year-ahead and 2-years-ahead change of log annual labour earnings. Coefficients are estimated using fixed effect OLS. Additional controls included in all equations : age dummies (5), occupation dummies (6), unemployment dummy, inactivity dummy, industry dummies (8), number of dependent children, number of adults in the households, number of household's members in paid employment (3), region dummies (17), wave dummies (17). The full set of results is provided in Appendix 2

2.4.2 Two different measures of uncertainty

In order to provide a picture of how temporary work relates to uncertainty, a measure for the latter is needed. In the analysis below I focus on two alternative proxies for earnings uncertainty commonly used in the applied literature: a measure of earnings variability (Carroll and Samwick, 1997, 1998) and the probability of future unemployment (Carroll et al., 2003).

The first of the two proxies is defined as the variability of the unexplained component of earnings growth, and is measured as the squared residual from the earnings growth regression (1-year-ahead) presented above. Using the variability of unexplained earnings growth as a proxy for uncertainty, however, presents some major drawbacks. Most importantly, observed fluctuations in unexplained earnings, or earnings growth, partly reflect unobserved heterogeneity or choices, and not only unavoidable risk (see, among others,Low et al., 2010). While unobserved heterogeneity can be dealt with by exploiting the longitudinal dimension of the data, over-estimation of the level of uncertainty is still likely, due the existence of superior information available to the agents. Guiso et al. (1992), and Dominitz (2001) propose a possible solutions to this second problem when detailed data about subjective probabilistic expectations are available. In this case, subjective earnings uncertainty can be indirectly measured as the variance of the subjective expected distribution of earnings.

While the coarseness of BHPS data on subjective expectations prevents this type of analysis, individual expectations reports can still be used to mitigate, at least partially, the issue. To the extent that these reports contain additional private information available to agents, they can be used to “filter-out” this information from the estimated residuals of the earnings growth regression (Ramos and Schluter, 2006). Following Ramos and Schluter (2006), I first run a simple test to check whether the former condition is met. The test is based on the following OLS regression:

Table 2.4: Filtering out private information form estimated residuals

	Estimated residual earnings growth $\hat{\varepsilon}_{it}$
ER_{it}= "worse than now"	-0.0427***
	[0.010]
ER_{it}= "better than now"	0.0196***
	[0.006]
Observations	17,812

Notes: Robust standart errors in brackets; The dependent variable is the estimated residual from the earnings growth regression (1-year-ahead). The regression is estimated using OLS

$$\hat{\varepsilon}_{it} = \pi_0 + \pi ER_{it} + \nu_{it} \tag{2.7}$$

where $\hat{\varepsilon}_{it}$ is the estimated residual from the earnings growth equation, and ER_{it} is the categorical variable representing expectation reports. If all the relevant information available to agents when forming expectations is contained in the information set available to the econometrician when estimating $\Delta ln\, y_{t,t+1}$, or if expectation reports are completely random, the vector $\hat{\pi}$ should be identically equal to zero. The results in table 2.4 below reject this hypothesis. The coefficients of the dummies for each category are statistically significant, and "well-behaved", exhibiting opposite signs with respect to the baseline category - "same as now".

The first measure of of the two measure of uncertainty is, then, computed using the "squared filtered residuals" as follows:

$$\hat{\nu}_{it}^2 = (\hat{\varepsilon}_{it} - (\hat{\pi}_0 + \hat{\pi} ER_{it}))^2 \tag{2.8}$$

Although the filtering procedure is undoubtedly a crude way to clean the residuals from private information, panel A of figure 2.1 shows that the derived measure $\hat{\nu}_{it}^2$ is actually capturing some subjective uncertainty. In the graph, the mean value of the variable is plotted against a categorical variable measuring workers' satisfaction about job security provided in the BHPS. The average values of the squared filtered residuals are decreasing with increasing reported levels of satisfaction with security, measured on a Likert-type scale from 1 to 7.

Panel B of the same figure compares, instead, the average values of the estimated measure of uncertainty in two groups defined by, respectively, individuals currently employed in temporary jobs, and with permanent contracts. Notwithstanding the potential limitations of the chosen measure, the graph clearly shows that individuals in temporary jobs exhibit a much higher degree of earnings uncertainty.[6]

In order to provide a more analytical picture, I estimate the following regression for the squared filtered residuals:

$$\hat{v}_{it}^2 = \gamma_0 + \gamma_{TW} TW_{it} + \gamma_x X_{it} + d_t + \xi_{it} \tag{2.9}$$

Given individual fixed effects have been already partialled out from the residuals of the earnings growth regression, they are excluded from the conditioning set of the above equation, which is estimated via OLS. The estimated γ_{TW} in table 2.5 (column 1) confirms what already visible in the plots. Temporary work is significantly associated to higher uncertainty. The conditional variance of the filtered residuals is 2.5 times larger for individuals in temporary work with respect to the baseline category represented by individuals employed with a permanent contract.

Concerning the second of the proposed measures of uncertainty, the probability of experiencing spells of unemployment is undoubtedly one of the most important among the possible sources of income risk. Although unemployment does not appear in the income process used for illustrative purposes in section 2.2, some authors have specifically used unemployment risk as a measure of uncertainty to quantify the importance of the precautionary motive for saving. Carroll et al. (2003), as a notable example, uses numerical

[6] Similar results are obtained if the sample mean is replaced by the median value in the two groups

techniques to obtain a consumption function which explicitly depends on the probability of job loss. The implications of Carroll's model are quite similar to the ones described in section 2.2. An increased unemployment risk lowers consumption and triggers assets accumulation for precautionary reasons.

Similarly to what seen for the first measure of uncertainty, Panel A in figure 2.2 shows the fraction of individuals currently employed who experience unemployment in the year following the interview, conditional on the reported level of satisfaction with job security. The graph clearly indicates a positive correlation between feelings of job insecurity and future job loss.

Panel B in the same figure compares, instead, the unconditional probability of unemployment in the twelve month after the interview for individuals in temporary jobs and individuals with permanent contracts. Only 2.5% of individuals currently employed with permanent contracts experience a spell of unemployment in the subsequent year, compared to the 12% of those in temporary jobs. Individuals in temporary jobs, however, can be potentially very different from individuals in permanent jobs on several dimensions which are likely to affect the probability of future unemployment spells. In order to account for these observable and unobservable differences, I estimate the following model for the conditional probability of unemployment:

$$Pr\left(U_{it+1}=1|Z_{it}\right)=F\left(\lambda_0+\lambda_{TW}TW_{it}+\lambda_x X_{it}+d_t+c_i+\varepsilon_{it}\right) \tag{2.10}$$

where Z_{it} is shorthand notation for the full conditioning set.

In the equation above, $U_{it+1}$is an indicator variable which takes value 1 if the individual experiences a spell of unemployment in the twelve month after the interview. Only individuals currently employed are included in the estimation sample. The model is estimated using a linear probability model with fixed effects, and a conditional fixed effect logit estimator. When the logit estimator is used, $F\left(\cdot\right)$ is the cumulative density function of the logistic distribution. When the linear probability model is estimated $F\left(\cdot\right)$ is simply the identity function.

The linear probability model should provide a good approximation for the conditional probability, and has the advantage of a straightforward interpretation of its coefficients in terms of marginal effects. On the other hand, the conditional fixed effect logit estimator accommodates both the discrete nature of the dependent variable and distribution-free unobserved heterogeneity, but comes at the cost of the impossibility to compute average partial effects.

The estimated $\hat{\lambda}_{TW}$ for both estimators is reported in columns 2 and 3 of table 2.5. Temporary work is found to be a statistically significant predictor of future unemployment spells. The estimated coefficient of the linear probability models implies that the probability of experiencing a spell of unemployment in in the next twelve months is 4.6 percentage points higher for individuals currently employed with a temporary contract. The effect, which might seem small in absolute terms, is quite big if compared to the average unconditional probability in the sample, roughly equal to 5%, implying a twofold increase.

The estimate obtained using the conditional logit estimator confirms the existence of a positive and statistically significant effect of temporary work on the probability of future unemployment. However, the impossibility to compute marginal effects prevents a comparison of magnitudes. [7]

[7] The huge drop of sample size is due to the "conditional" nature of the estimator: only observations with an actual change in the dependent variable contribute to the likelihood function.

Figure 2.1: Squared filtered residuals

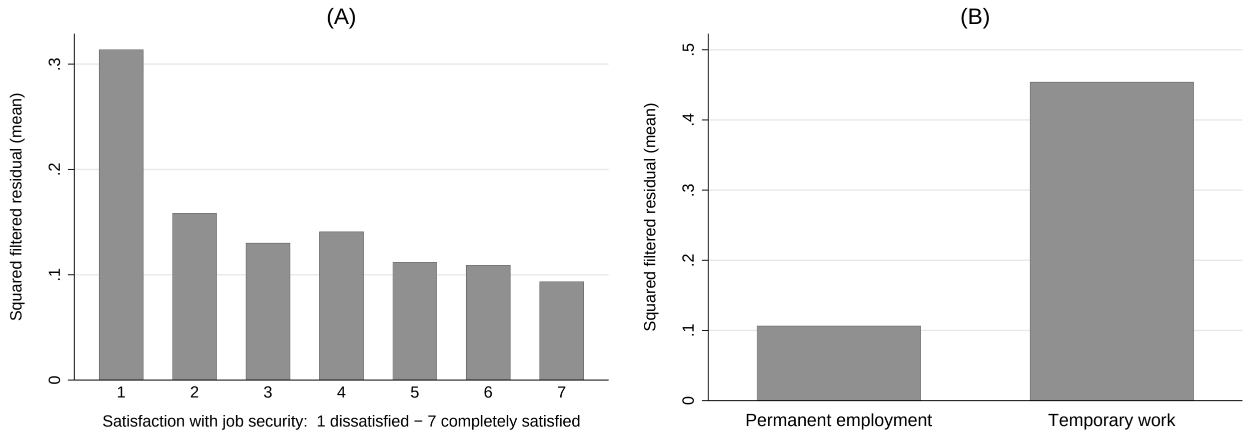

Figure 2.2: Unemployment in the twelve months after the interview

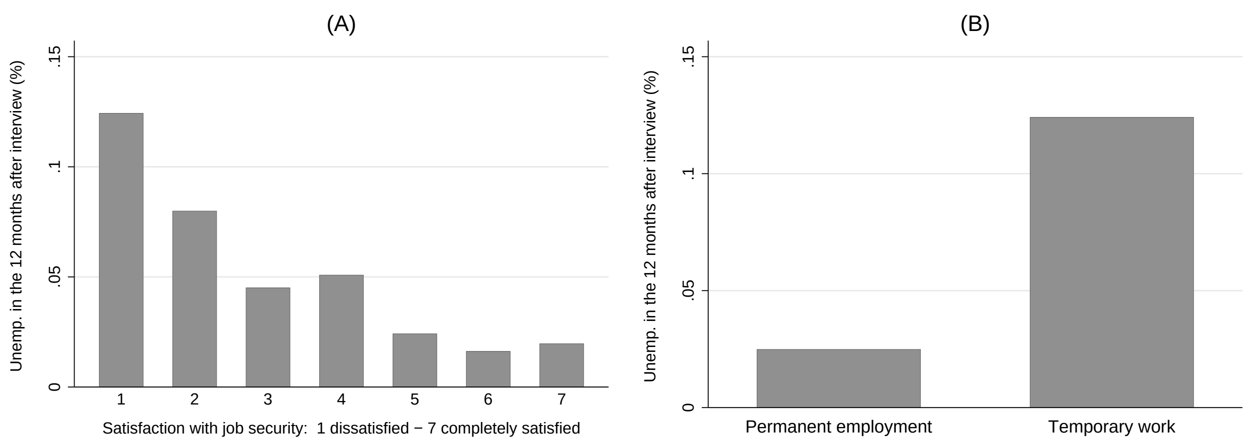

Table 2.5: Temporary work and uncertainty

	Squared filtered residuals	Unemp. prob. in the 12 month after interview	
	$\hat{v}_{it}^2$	$Pr(U_{it+1}=1)$	
	OLS	FE OLS (LPM)	FE Logit
	(1)	(2)	(3)
Temporary work	0.3563***	0.0542***	1.1557***
	[0.080]	[0.009]	[0.276]
Additional controls	yes	yes	yes
Fixed effects	no	yes	yes
Observations	17,812	17,320	2,472
Units	3,317	3,307	363

Notes: Robust standart errors in brackets; Column (1) dependent variable is the squared filtered residual from the earnings growth equation (1-year-ahead). Column (2) and (3) dependent variable is a dummy variable taking value 1 is the individuals has experienced a spell of unemployment in the 12 months after the interview. dditional controls included in all equations : age dummies (5), occupation dummies (6), unemployment dummy, inactivity dummy, industry dummies (8), number of dependent children, number of adults in the households, number of household's members in paid employment (3), region dummies (17), wave dummies (17). The full set of results is provided in Appendix 2

2.5 Consumption and saving

The evidence provided in the previous section shows that household heads in temporary work tend to have lower earnings, higher earnings growth, and higher uncertainty. Since subjective expectations are consistent, on average, with future earnings growth, the results also suggest that the latter is likely to be anticipated. As discussed in the introduction, this mirrors the two contrasting effects of temporary work for workers' welfare documented in the literature. Whether a stepping stone towards better jobs effect is perceived by workers, and, most importantly, it dominates over perceived insecurity about the future is the question addressed in this section.

I exploit the insights from the simple model described in section 2.2: if earnings are temporarily low, saving should decrease in order to smooth consumption in anticipation of higher expected future income; higher uncertainty, in contrast, should translate into higher saving for precautionary reasons. Consumption and saving choices can, then, be used to assess which of these two effects dominates.

2.5.1 The saving function

As mentioned in section 2.3, the reduced form of the saving function is estimated using data on household's average monthly saving as in Guariglia (2001), Guariglia (2002), Rossi (2009), Klemm (2012), and Giavazzi and McMahon (2012). [8]

A major problem encountered when dealing with saving data is the likely mass point at zero, leading to non-linearity of the conditional mean. The sample considered in this paper is a clear example, with 51% of households reporting zero monthly savings.

A common approach in the applied literature is to estimate the conditional mean using a Tobit estimator. However, the Tobit estimator comes at the cost of some restrictive assumptions, namely normality and homoschedasticity. Using the OLS estimator on the log-transformed data is another possible solution, but would would translate in discarding a big fraction of the data. Transformations of the type $ln(a+y)$ would not solve the problem in the latter case. They might solve the numerical one, but are likely to affect estimation in a non-sensible way.

In order to overcome these difficulties, the reduced form of the saving function is estimated using a Poisson Quasi Maximum Likelihood estimator. The choice of the estimator is driven by some characteristics of Poisson QMLE which make it an ideal candidate for the task: i) the estimator does not require the outcome to be Poisson-distributed in order to be consistent (Wooldridge, 2010a; Cameron and Trivedi, 2009) ; ii) it does a good job in dealing with big zero mass points (Silva and Tenreyro, 2011). On top of that, Poisson QMLE is superior to other non-linear estimators in that it does not suffer the incidental parameters

[8] A common practice in the applied literature dealing with precautionary savings is to estimate reduced form equations where assets holdings are regressed on a measure of risk. BHPS data, however, do not contain information about the stock of wealth in a panel dimension. Information regarding wealth holdings and outstanding debt is available only for 1995, 2000 and 2005. This makes it difficult to compare wealth holdings among individuals who may have entered the labour market at different points in time. However, saving flows and stocks of wealth are, in principle, connected through the budget constraint.Guiso et al. (1992) suggest that focusing separately on the effects of uncertainty on the flow of savings and on the stock wealth may serve as a double test of the theory of precautionary savings.

problem, and allows fixed effect estimation of the saving function. The assumption necessary for the estimator to be consistent, other than non-negativity of the outcome, is an exponential parametrization for the conditional mean of the saving flow. The latter can be written as:

$$E\left(S_{it}|Z_{it}\right) = \exp\left(\alpha^{s}_{TW} TW_{it} + \alpha^{s}_{X} X_{it} + c_i + d_t\right) \tag{2.11}$$

One limitation of this approach is that it assumes that the observed zeroes in the data are actual zeroes (i.e. corner solutions) rather than the result of censoring. Since BHPS data only contains information about active saving, it is not possible to verify if individuals who report not to be active savers have actual negative savings. Classifying households with negative saving as non-savers might lead to understate or overstate the magnitude of the effect of temporary work. If households switch from positive/zero saving to negative saving when the head is in a temporary job, estimates of the saving equation will provide a lower-bound for the true consumption smoothing effect. If, instead, households react by decreasing the amount of outstanding debt, but remaining under the zero-saving threshold, misclassifying negative saving as zero will bias estimates against the existence of a precautionary motive. In this latter case, however, estimates of the consumption equations should be able to capture the precautionary response to the extent that the resources used to reduce the amount of debt are diverted from expenditures measured in BHPS data.

The vector X_{it} in the equation above includes the same set of individual and household's characteristics used in the previous section. Additional regressors are a categorical variable for housing tenure, household earnings (log) , earnings of the household head (log), a dummy variable for benefit income in the household, a set of financial situation indicators controlling for financial constraints, and the same set of indicators for subjective expectations about future economic conditions seen in section 2.4 - which are added here to help controlling for standard life-cycle reason for saving.

On top of this set of controls, unobserved heterogeneity is accounted for via household head-specific fixed effects. As mentioned in the introduction, fixed effect estimation of the saving function is important for two main reasons. On the one hand, if selection into temporary jobs is guided by unobservable characteristics, like risk aversion, not fully accounted for by the set of covariates, fixed effects should mitigate the self-selection problem to the extent that these characteristics are time-invariant. On the other hand, fixed effects, along other major determinants of life-time income, should be able to account, at least partially, for permanent income. In this case, the inclusion of the current level of earnings should approximate the effect of the transitory component of income. This latter consideration will be further discussed when interpreting the results.

2.5.2 The consumption function

The empirical analysis of household's consumption, revolves around the estimation of a reduced form of the consumption function described in section 2.2. Following Miles (1997) and Benito (2006) the reduced form to be estimated can be expressed as:

$$log(C_{it}) = \alpha_0^c + \alpha_{TW}^c TW_{it} + \alpha_X^c X_{it} + c_i + d_t + \upsilon_{it} \tag{2.12}$$

The conditioning set in the RHS of the above equation is identical to the one described earlier for the saving function, and the same arguments apply here. The dependent variable requires, instead, some additional considerations. In the ideal setup, C_{it} would measure all types of expenditures for each household at each time period, providing a picture of the chosen consumption path. While the longitudinal structure of the BHPS allows to follow individuals (and households) through time, availability of data about consumption is, however, limited.

As anticipated in the data description, two alternative definitions of consumption are used, and estimation of the consumption function is performed separately for each definition.

When the first variable - CONS1 - is used, C_{it} corresponds to household's average monthly expenditures on food and grocery. Given the latter are likely to be less income elastic than other categories of consumption, some concerns may rise about the actual responsiveness of this type of expenditures to uncertainty about future earnings[9]. Put differently, one may argue that, in times of uncertainty, it might be unlikely that households cut back on basic needs. Although this could potentially bias the results against the existence of a precautionary motive, Benito (2006), using the same BHPS data, finds significant evidence consistent with the hypothesis that unemployment risk depresses food and grocery expenditures. The estimated coefficient implies that a 1 percentage point increase in the probability of being unemployed decreases current consumption by 0.7 percent.

In order to overcome this potential limitation, a second broader measure of non-durable consumption is also provided, closer to the used by Guiso et al. (1992). In this second case, C_{it} is the aggregation of food and grocery expenditures, rent/mortgage repayments, oil/gas/electricity bills, expenditures for leisure activities, and expenditures for outside meals. Part of this additional information is available, however, only for waves 7-18 of the survey, so that the consumption function estimated using CONS2 is relative to a subsample of observations.

Given the concerns about self selection of individuals in temporary jobs, the reduced forms are estimated using an OLS estimator with household head-specific fixed effects, differently from Benito (2006). The use of the log-linear specification should not create estimation troubles given virtually no zero is observed in the data.

2.5.3 Results and interpretations

The results in table 2.6 show that, compared to permanent employment, temporary work for the head of the household is associated, on average, with roughly 15% less saving [10]. The magnitude of the effect is similar in all specifications but the ones in columns 3, 4, and

[9]Paluch et al. (2012), using data from the Family Expenditure Survey 1974-1993,show that the income elasticity of expenditures for food and grocery ranges between 0.13 and 0.23 in the period considered.

[10]Given the nature of Poisson QMLE, the formula $(e^{\beta} - 1) \times 100$ is used to calculate the effect of an indicator variable, where β is the estimated coefficient. It represents the average percentage increase/decrease in the dependent variable passing from 0 to 1. The effects of all indicator variables used in estimation performed using Poisson QMLE are computed in the same way

7. Notably, when household earnings are added to the set of controls, the coefficient on the dummy variable for head of the household in temporary work drastically drops. The non significance of the dummy in these two specifications, however, is not due to a lack of precision. The estimated standard errors are, indeed, constant across specifications, if not marginally lower in column 7. The results suggest, instead, that the lower level of saving initially associated to temporary work entirely driven by the lower level of transitory income associated to temporary work. Once transitory income is accounted for in estimation, no significant difference appear to exist between temporary work and permanent employment in terms of savings accumulation.

This result can be interpreted in the light of the predictions from the simple model presented in section 2.2, combined with the evidence provided in section 2.4. From section 2.4 we know that temporary work entails a temporarily low earnings followed by an expected future increase. What equation 4 predicts is that, in absence of uncertainty, and everything else being equal, this should induce households to save less to smooth consumption between periods. The initially observed difference in saving associated to temporary work, and its sensitivity to the inclusion of current earnings, suggest that this mechanism is at play.

This interpretation, however, holds only to the extent that temporary work for the household head is uncorrelated with idiosyncratic shocks to savings potentially captured by household earnings (e.g. partner's labour supply and earnings). In order to address this concern, the same equation is estimated using earnings of the head instead of household earnings. Results in column 4 show that the coefficient on the temporary work dummy is almost unchanged.

The lack of a significant positive effect of temporary work on saving, once earnings are accounted for, further indicates that the higher uncertainty associated to temporary work documented in section 2.4, does not trigger savings accumulation for precautionary reasons. More precisely, compared to permanent employment, temporary work is not associated to a stronger precautionary motive for saving. It is important to notice that the estimated saving function does not embed a proxy for uncertainty in any of the presented specifications. The objective, in fact, is not to test for the existence of precautionary savings, but to test whether temporary employment entails extra saving for precautionary reasons. This test does not require a proxy for risk. To the extent that the documented increased uncertainty translates into extra saving compared to permanent employment, the temporary work dummy should exhibit a positive coefficient once other potential determinants of saving are accounted for. The results in table 2.6 clearly reject this hypothesis.

Estimates of the consumption functions provide further evidence of consumption smoothing, and the absence of a stronger precautionary saving motive. If the interpretation suggested above is correct, which is to say is if temporary work solely entails consumption smoothing in anticipation of higher future earnings, then it should not have any effect on households consumption which is almost insensitive to transitory variations of earnings. This is what we empirically observe in the sample. Temporary work for the household head is not statistically significant in all but one of the specifications presented in table 2.7. It is worth noting that these conclusions crucially hinge on the ability to account of unobservable determinants of consumption and saving potentially correlated with contract type, and on the possibility to interpret current earnings as the transitory component of income. The choice of fixed effect estimation of both the consumption and saving functions is mainly driven by these considerations.

In a pure cross-section setup, differences in the amount of saving and consumption between heads in temporary jobs and individual in permanent employment could, indeed, be due to differences in permanent income, as well as to different attitudes towards risk, or differences in prudence and time preferences. In order to isolate the response of saving to transitory variations in earnings we would need to first construct a credible proxy for long-run income, and then compute transitory earnings as the difference between the observed level and the predicted permanent component. To solve the endogeneity problem associated to unobservables would, instead, require some exogenous variation in the contract type.

Focusing on within variations, together with accounting for a rich set of controls for major determinants of long-run income and resource accumulation, offers an alternative solution. To the extent that the permanent income, as well the mentioned unobservables, remain constant along the observation period, fixed effect estimation should be able to account for their effect on the two outcomes. Current earnings should, then, pick up the desired transitory component of income. While the latter measure is not free from measurement error, this problem is also likely to plague commonly used estimates of permanent income, which have been shown to be highly sensitive to the predictors used in estimation (Alan et al. 2014).

Comparing the magnitude of the estimated coefficients of log earnings in the saving and consumption equations helps to strengthen this interpretation. The coefficient reported in last column of table 2.6 implies an elasticity of saving to household earnings roughly equal to 0.65. Looking at the estimated consumption functions, the elasticity is instead, equal to 0.02 both for food and grocery expenditures, and the broader definition of consumption. The asymmetric response of consumption and saving is consistent with the predictions of the standard life-cycle model: consumption is nearly insensitive to variations in transitory income, while saving is fully responsive to differences between current and permanent income.

The coefficients of the remaining variables in table 2.6 and 2.7 are in line with what expected.

The indicator dummy for benefit income is included in estimation to account for the fact that temporary workers are potentially more likely to receive some form of income support given the lower level of income and the likelihood of unemployment spells. The presence of a welfare safety net might, in principle, distort saving decisions, as shown by Engen and Gruber (2001) for unemployment insurance in the US. Consistently with the "crowd-out" effect found by the two authors, the results show that households who receive some income support in the form of benefits tend to save less, although the effect becomes insignificant once household earnings are included. The decreased level of saving is also accompanied by a positive effect on food and grocery expenditures, as can be seen in panel A of table 2.7.

The level on monthly saving, and consumption to a much lower extent, is shown to be monotonically decreasing with worsening of the financial situation, the reference category being heads of the household reporting to be "managing alright" or "comfortably". The variable is included in estimation as an and subjective measure of financial constraints. In the last specification in table 2.6, financial situations reported to be "quite or very difficult", and "just getting by" are associated with, respectively, 50% and 36% lower average monthly saving. Financial constraints have a much lower, although still significant, effect on consumption. The response is roughly equal to -2 % for for both food and grocery the broader measure of consumption when the head reports mild financial difficulties ("just getting by"). When severe financial difficulties are considered, the corresponding figure ranges between -5% and -6% . The different response of saving and consumption to financial constraints can be seen as a further confirmation of consumption smoothing.

The sign of the coefficients for the two indicator variables measuring expectations regarding future economic conditions are consistent with the permanent income hypothesis in the saving equation. However, only the dummy for expected worsening of future economic conditions attracts a statistically significant coefficient, indicating 6% more saving on average. Concerning consumption, the coefficients imply a lower level of expenditures associated to optimistic expectations. It is worth notice that, although this result is in contrast with predictions from the standard permanent income hypothesis, the estimated effect - roughly 1% - is quite small.

Table 2.6: Saving function - coefficients of interest

Real monthly saving	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Head in temporary work	-0.1679**	-0.1676**	-0.0674	-0.0666	-0.1631**	-0.1516**	-0.0540
	[0.066]	[0.066]	[0.064]	[0.066]	[0.066]	[0.065]	[0.063]
Unemployment rate		0.0044					0.0049
		[0.008]					[0.008]
Log household earnings			0.6419***				0.5950***
			[0.044]				[0.042]
Log head's earnings				0.3262***			
				[0.039]			
Benefit income dummy					-0.0759**		-0.0345
					[0.034]		[0.034]
Fin. Exp.: "worse"						0.0763***	0.0665**
						[0.029]	[0.027]
Fin. Exp.: "better"						-0.0176	-0.0025
						[0.021]	[0.020]
Fin. Sit.: "quite/very difficult"						-0.6947***	-0.6100***
						[0.104]	[0.101]
Fin. Sit: "just getting by"						-0.4476***	-0.4036***
						[0.036]	[0.034]
Additional controls	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes
Observations	20,023	20,023	20,023	20,023	20,023	20,023	20,023
Units	2,784	2,784	2,784	2,784	2,784	2,784	2,784

Notes: Robust S.E. in brackets; The dependent variable is the household's real average monthly saving flow (£). Unit of observation is the head of the HH. The equations are estimated using fixed effects Poisson QMLE. Additional controls included in all shown specifications: age dummies (5), occupation dummies (6), unemployment dummy, inactivity dummy, industry dummies (8), number of dependent children, number of adults in the households, number of household's members in paid employment (3), tenure dummies (3), region dummies (17), wave dummies (17). The full set of results is provided in Appendix 2

Table 2.7: Consumption functions - coefficients of interest

Panel A: CONS1	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Head in temporary work	-0.0249	-0.0251	-0.0191	-0.0193	-0.0264*	-0.0242	-0.2301
	[0.016]	[0.016]	[0.015]	[0.015]	[0.016]	[0.016]	[0.015]
Unemployment rate		-0.0021					-0.0018
		[0.002]					[0.002]
Log total household earnings			0.0233***				0.0235***
			[0.008]				[0.008]
Log head's earnings				0.0168***			
				[0.006]			
Benefit income dummy					0.0455***		0.0489***
					[0.008]		[0.008]
Fin. Exp.: "worse"						0.0083	0.0080
						[0.007]	[0.007]
Fin. Exp.: "better"						-0.0169***	-0.0164***
						[0.005]	[0.005]
Fin. Sit.: "quite/very difficult"						-0.0514***	-0.0497***
						[0.012]	[0.012]
Fin. Sit: "just getting by"						-0.0211***	-0.0202***
						[0.006]	[0.006]
Additional controls	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes
Observations	22,913	22,913	22,913	22,913	22,913	22,913	22,913
Units	3,585	3,585	3,585	3,585	3,585	3,585	3,585

Panel B: CONS2	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Head in temporary work	-0.0216	-0.0216	-0.0149	-0.0164	-0.0214	-0.0215	-0.0154
	[0.013]	[0.013]	[0.013]	[0.014]	[0.013]	[0.013]	[0.013]
Unemployment rate		0.0003					0.0004
		[0.002]					[0.002]
Log total household earnings			0.0261***				0.0239***
			[0.006]				[0.006]
Log head's earnings				0.0157***			
				[0.005]			
Benefit income dummy					-0.0051		-0.0017
					[0.007]		[0.007]
Fin. Exp.: "worse"						0.0023	0.0017
						[0.007]	[0.007]
Fin. Exp.: "better"						-0.0111**	-0.0105**
						[0.005]	[0.005]
Fin. Sit.: "quite/very difficult"						-0.0595***	-0.0573***
						[0.011]	[0.011]
Fin. Sit: "just getting by"						-0.0206***	-0.0187***
						[0.005]	[0.005]
Additional controls	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes
Observations	15,102	15,102	15,102	15,102	15,102	15,102	15,102
Units	3,015	3,015	3,015	3,015	3,015	3,015	3,015

Notes: Robust S.E. in brackets; The dependent variable in panel A is the log of CONS1 - food and grocery expenditures. The dependent variable in panel B is the log of CONS2 - obtained aggregating food and grocery expenditures, rent and mortgage repayments, oil/gas/electricity bills, and expenditures for leisure and outside meals; Unit of observation is the head of the HH; In panel B only observation from waves 7-18 are used due to availability of additional information about consumption; All specifications are estimated via fixed effects OLS estimator; Unit of observation is the head of the HH. The equations are estimated using fixed; age dummies (5), occupation dummies (6), unemployment dummy, inactivity dummy, industry dummies (8), number of dependent children, number of adults in the households, number of household's members in paid employment (3), tenure dummies (3), region dummies (17), wave dummies (17). The full set of results is provided in Appendix 2

2.6 Conclusions

The objective of this paper was to provide a new empirical approach to the consequences of temporary work for workers' welfare. Rather than focusing on transition rates observed ex-post, as common practice in the literature, consumption and saving choices are used as a measure of future prospects to understand whether temporary work is perceived by workers as a stepping stone towards better jobs, or solely as a source of uncertainty and insecurity.

Differently from the observation of workers' trajectories, the proposed approach offers the possibility to understand how workers perceive the consequences of temporary work for their welfare, while providing an new method to contrast the stepping stone versus the dead end effect.

The evidence provided in the paper indicates that, compared to permanent employment, temporary work is associated with temporarily lower earnings, and higher expected income growth. On the other hand, temporary work is also shown to entail a higher likelihood of experiencing future spells of unemployment, and a higher variability of the unexplained component of income growth, two commonly used measures of uncertainty.

In order to understand which of these two conflicting effects is prevailing, I resort to the economic theory of consumption and saving choices. To the extent that individuals are rational and forward-looking, saving and consumption can act as sufficient statistics for agents' expectations, and their willingness to insure against perceived uncertainty.

Estimates of the reduced forms for consumption and saving functions indicate that households whose head is currently employed in a temporary job, smooth consumption in anticipation of higher future earnings, consistently with the permanent income hypothesis. The initially observed lower level of saving associated with temporary work is, indeed, entirely driven by a lower transitory income.

Overall, the results provided in the paper point to a stepping stone for temporary work, consistently with previous evidence for Britain in Booth et al. 2002. Most importantly, the evidence provided indicates that this effect is actually perceived by individuals, and internalized in their behaviour.

Chapter 3

Poisson regressions in panel data: random effects or fixed effects, when is that the question?

Introduction

The robustness properties of the Poisson Quasi Maximum Likelihood Estimator (QMLE) are a well-established result in the econometrics literature. Wooldridge (1997), applying the general results by Gourieroux, Monfort and Trognon (1984), shows that, other than correct specification of the conditional mean and non-negativity of the outcome, consistency of Poisson QMLE does not require a Poisson distribution, nor even discreteness.

An important feature of the estimator, in the context of panel data, is that it does not suffer the "incidental parameter problem" common to the vast majority of non-linear estimators. This allows the practitioner to estimate models where time-constant unobserved heterogeneity is arbitrarily dependent on covariates. As it is always the case with fixed effect estimators, however, one obvious limitation is the impossibility to estimate the effects of time-invariant characteristics. Given the time-invariant variables cancel out in quasi demeaning transformations, the relative coefficient can not be identified.

A readily-available option for the practitioner is to estimate the model using the Poisson random effects Maximum Likelihood Estimator (MLE). This treats heterogeneity as a nuisance parameter of the likelihood function, independent of covariates. Making a particular parametric assumption about the distribution of the unobserved heterogeneity (a Gamma distribution in the Poisson case) leads to a closed form solution for the joint likelihood of the outcome, the covariates and unobserved heterogeneity. The latter can then be integrated out under the assumption of independence. The possibility to estimate the effect of time-invariant characteristics, however, comes at the cost of the strong assumption of independence between covariates and unobserved heterogeneity. If this assumption is violated, the estimator is inconsistent for the true parameter of the conditional mean.

However, some contributions in the empirical literature have noticed that, when the time dimension of the panel gets bigger, the Poisson Random Effects (RE) and Fixed Effects (FE) estimator tend to produce very similar results. This can be explained looking at the first order conditions for the two estimators. As it will be described in the next section, they differ by a term which is a function of the time dimension, T, and the variance of the assumed (Gamma) distribution of unobserved heterogeneity, σ_a^2. When $T \to \infty$, or $\sigma_a^2 \to \infty$, the FOC of the Poisson RE estimator are equivalent to the ones of the Poisson FE estimator.

The objective of this paper is to investigate the applicability of this approximation in common panel data where the number of time periods if finite, although potentially large, and the practitioner has no a priori knowledge about the distribution of unobserved heterogeneity. In order to do so I use a Monte Carlo study that combines various values of T and σ_a^2 under different Data Generating Processes (DGP's). Given that one of the main reasons for using the RE estimator is the possibility to estimate the coefficients on time-constant variables, a time-constant dummy is embedded in the conditional mean for the outcome in each DGP, together with two time-varying variables. All the considered DGP's allow for a non-zero correlation between the unobserved heterogeneity and each covariate, making the RE estimator biased and inconsistent.

The results of the Monte Carlo experiments confirm that increasing the values of both T and σ_a^2 decreases the bias of RE estimates. The estimated coefficients on the time-varying variables obtained using the RE estimator are found to be very close to the ones obtained using the FE estimator under reasonable values of T , although the goodness of the approximation crucially depends on σ_a^2.

The experiments, however, show that the estimated coefficient on the time-constant dummy obtained using the RE estimator exhibits substantial bias in all the considered cases. This result is important for practitioners. Given the similarity between the estimated coefficients on the time-varying variables obtained using the two estimators in some realistic scenarios, an Hausman test might induce the practitioner to choose a RE parametrization. The evidence provided indicates that the estimated coefficients on time-constant variables should be interpreted with caution if these are suspected to be correlated with unobserved heterogeneity.

The results also show that, with respect to the time-varying covariates, the efficiency gains associated with RE estimation tend to vanish with increasing levels of T and σ_a^2. The coefficient on the time-constant dummy variable, however, exhibits increasing standard errors leading to an identification problem in the limit.

The chapter is structured as follows: Section 3.1 provides a description of the two estimators. Section 3.2 presents the experimental design. the results of the Monte Carlo study are presented in section 3.3. Section 3.4 concludes.

3.1 The two estimators

In order to describe the two estimators it is useful to start from the simplest parametric framework which is standard in count data contexts. Count data models are extensively used in a wide range of applications including models for healthcare utilization (measured as the number of doctor visits), models for firm's level of innovation (proxied by the number of patents), fertility equations (number of children), and economic models of crime (measured by the number of arrests or convictions). The basic Poisson regression model with unobserved effects assumes that:

$$y_{it}|\mathbf{x}_i, a_i \sim Poisson\left[a_i \lambda\left(\mathbf{x}_{it}, \beta\right)\right] \tag{3.1}$$

where y_{it} is the outcome, x_{it} is a vector of individual characteristics with the associated coefficient vector β, and a_i represents time-invariant individual-specific unobserved heterogeneity. The conditional mean of the outcome can be written as:

$$E\left[y_{it}|\mathbf{x}_{it}, a_i\right] = a_i \lambda\left(\mathbf{x}_{it}, \beta\right) \tag{3.2}$$

The most common parametrization of the mean function for the Poisson regression model is the exponential, according to which:

$$\lambda\left(\mathbf{x}_{it}, \beta\right) = \exp\left(\mathbf{x}_{it}'\beta\right) \tag{3.3}$$

It is clear from equation (3.2) that individual-specific heterogeneity, represented by a_i, enters the conditional mean multiplicatively , rather than additively as in the standard linear case. However, given the exponential parametrization of the conditional mean, individual effects can still be interpreted as intercept shifters. To see this, equation (3.2) can be rewritten according to:

$$a_i \exp\left(\mathbf{x}_{it}'\beta\right) = \exp\left(v_i + \mathbf{x}_{it}'\beta\right)$$

where $v_i = \ln\left(a_i\right)$

Depending on the assumptions made about the joint distribution of a_i and $\mathbf{x}_{it}$, the parameters of the conditional mean can be consistently estimated with either the Poisson FE or

Poisson RE estimator. They will now be described in turn.

3.1.1 Poisson FE

The Poisson FE estimator was first developed as a Conditional Maximum Likelihood Estimator (CMLE) by Hausman, Hall and Griliches (1984). The estimator is obtained using an orthogonal re-parametrization, which exploits $\eta_i \equiv \sum_{t=1}^{T} y_{it}$ as a sufficient statistic for a_i. They show that, for $y_{it} \sim Poisson\left[a_i \lambda\left(\mathbf{x}_{it}, \beta\right)\right]$, the joint density of $y_{i1}, \ldots, y_{iT}$, conditional on η_i, can be re-written as a multinomial density:

$$f\left(\mathrm{y}_i | \mathbf{x}_i, \beta, \eta_i\right) = \frac{\eta_i!}{\prod_{t=1}^{T} y_{it}} \times \prod_{t=1}^{T} \left(\frac{\mu_{it}}{\sum_{s=1}^{T} \mu_{is}}\right)^{y_{it}}$$

where $\mu_{it} = a_i \exp\left(\mathbf{x}_{it}' \beta\right)$. The results is that a_i, as well as any other time-constant variable, cancels out in the ratio $\mu_{it} / \sum_{s=1}^{T} \mu_{is}$, so that the joint conditional density does not depend on unobserved effects. The model is then estimated maximizing the resulting conditional log-likelihood. Excluding the terms not depending on β, the latter can be written as:

$$\mathscr{L}\left(\beta\right) = \sum_{i=1}^{N} \ell_i\left(\beta\right) \propto \sum_{i=1}^{N} \sum_{t=1}^{T} y_{it} \ln\left(\frac{\mu_{it}}{\sum_{s=1}^{T} \mu_{is}}\right) \tag{3.4}$$

It can be shown that differentiation of the conditional likelihood leads to FOC:

$$\sum_{i=1}^{N} \sum_{t=1}^{T} \mathbf{x}_{it} \left(y_{it} - \frac{\bar{y}_i}{\bar{\lambda}_i} \lambda_{it}\right) = \mathbf{0} \tag{3.5}$$

Blundell, Griffith and Windmeijer (2002) show that the log-likelihood of Poisson CMLE in equation (3.4) is proportional to the one that one would obtain using Poisson MLE that treats a_i as parameters to be estimated. Poisson FE MLE is obtained by maximization of the concentrated log-likelihood (terms not involving β are dropped for simplicity):

$$\mathscr{L}_c\left(\beta\right) = \sum_{i=1}^{N} \ell_i\left(\beta, \hat{a}_i\left(\beta\right)\right) \propto \sum_{i=1}^{N} \sum_{t=1}^{T} y_{it} \ln\left(\frac{\mu_{it}}{\sum_{s=1}^{T} \mu_{is}}\right) \tag{3.6}$$

In the above expression, $\hat{a}_i\left(\beta\right)$ is the ML estimator of a_i obtained by differentiating and setting to to zero the log-likelihood associated with the joint density of $y_{i1}, \ldots, y_{iT}$, with $y_{it} \sim Poisson\left[\mu_{it}\right]$, and can be written as:

$$\hat{a}_i(\beta) = \frac{\sum_{t=1}^{T} y_{it}}{\sum_{t=1}^{T} \lambda_{it}} = \frac{\bar{y}_i}{\bar{\lambda}_i}$$

Equation (3.6) leads to FOC identical to those in equation (3.5). This results shows that, differently from the majority of non-linear estimators, Poisson FE does not suffer the incidental parameters problem, i.e. inconsistent estimation of a_i does not contaminate estimates of β.

One important consideration about Poisson FE MLE and CMLE is that both estimators are derived under the assumption that $y_{it} \sim Poisson\left[a_i \lambda\left(\mathbf{x}_{it}, \beta\right)\right]$ (which I will refer to as the "Poisson assumption"), and the assumption that y_{it} and y_{is} are independent conditional on $\mathbf{x}_i$ and a_i for all $r \neq t$ (which I will refer to as the "serial conditional independence assumption"). However, as shown in Wooldridge (1999), the only requirement for consistency of the estimator is correct specification of the conditional mean $E\left[y_{it}|\mathbf{x}_{it}, a_i\right]$. Importantly the distribution of the outcome need not be Poisson or discrete. Correct inference, however, should be based on the usual robust variance matrix estimator when deviating from the Poisson assumption or the serial conditional independence assumption.

Finally, it is worth noting that the same FOC in equation (3.5) can be obtained by applying a quasi-demeaning transformation to to equation (3.2). As shown by Cameron and Trivedi (2013), the Poisson FE estimator can be, then, obtained as the method of moments estimator that solves the sample analog of the moment conditions:

$$E\left[\mathbf{x}_{it}\left(y_{it} - \frac{\bar{y}_i}{\bar{\lambda}_i}\lambda_{it}\right)\right] = \mathbf{0}$$

3.1.2 Poisson RE

The Poisson RE estimator considered in this study is the one introduced by Hausman, Hall and Griliches (1984). The estimator treats unobserved heterogeneity, a_i, as a random variable with a specified distribution, $g(a_i|\pi)$ depending on the parameter vector π. Independence of unobserved heterogeneity on observables (which I will refer to as the "RE assumption") allows a_i to be integrate out of the joint density $f(\mathrm{y}_i|\mathbf{x}_i, \beta, a_i, \pi)$, giving an unconditional (on a_i) joint density:

$$f(\mathrm{y}_i|\mathbf{x}_i, \beta, \pi) = \int [f(y_i|\mathbf{x}_i, \beta, a_i)]\, g(a_i|\pi) da_i = \int \left[\prod_t f(y_{it}|\mathbf{x}_i, \beta, a_i)\right] g(a_i|\pi) da_i \quad (3.7)$$

The integral has a closed form solution (leading to a marginal negative binomial model) when the Poisson assumption and the serial conditional independence assumption are maintained, together with:

$$a_i \sim Gamma(\delta, \delta) \quad (3.8)$$

under which $E[a_i] = 1$ and $V[a_i] = 1/\delta$.

The parameters β and δ are estimated by maximizing the log-likelihood associated with joint unconditional density. The FOC characterizing the RE estimator can be expressed as:

$$\sum_{i=1}^{N} \sum_{t=1}^{T} \mathbf{x}_{it} \left(y_{it} - \lambda_{it} \frac{\bar{y}_i - \delta/T}{\bar{\lambda}_i - \delta/T} \right) = \mathbf{0} \quad (3.9)$$

3.1.3 Comparing the two estimators

Comparing equation (3.9) and equation (3.5), it can be noticed that the two sets of first order conditions differ by the term δ/T that appears in equation (3.9) for the RE case. Given the RE Poisson estimator is derived under the assumption of a Gamma distribution for a_i, the term δ is equal to the inverse of the unobserved heterogeneity variance, thus $\delta/T = 1/\sigma_a^2 T$. It follows immediately that the RE estimator for β is equivalent to the FE estimator when $1/\sigma_a^2 T \to 0$, which is to say when either $T \to \infty$, or $\sigma_a^2 \to \infty$.

The similarity to OLS is striking. In this case the RE estimator is the FGLS estimator obtained by an OLS regression of $(y_{it} - \theta \bar{y}_i)$ on $(x_{it} - \theta \bar{x}_i)$, where:

$$\theta = 1 - \left\{ 1 / \left[1 + T \left(\sigma_a^2 / \sigma_u^2 \right) \right] \right\}^{1/2} \tag{3.10}$$

It is easy to see that when the term θ approaches unity, that is to say when $T \to \infty$, or $\sigma_a^2 / \sigma_u^2 \to \infty$, the FGLS estimator converges to the FE OLS estimator.[1] Blundell and Windmeijer (1997) show this result using spatially-clustered data on hospital utilization, where G - the cluster dimension - substitutes for T.

In a maximum likelihood framework, the role played by T and σ_a^2 can be better understood from a Bayesian perspective. Following Arellano and Bonhomme (2011), given equation (3.7), the generic RE ML estimator can be written as the solution to:

$$\hat{\beta}^{RE} = \arg\max_{\beta} \left(\arg\max_{\delta} \sum_{i=1}^{N} \ln \int \left[f\left(y_i | \mathbf{x}_i, \beta, a_i \right) \right] g(a_i | \pi) da_i \right) \tag{3.11}$$

From a Bayesian perspective the estimator coincides with the mode of the posterior distribution (marginal likelihood) of β, where $g\left(a_i | \pi \right)$ is the (hierarchical) prior specification for the individual effects. In the Poisson RE case, a_i is assumed to follow a Gamma distribution characterized by hyperparameter δ, which is the natural conjugate prior for the Poisson distribution. The intuition offered by the Bayesian perspective is that the contribution of the prior to the posterior distribution of β depends on both T and σ_a^2.

Concerning T, the log-likelihood function in equation (3.11) is a sum of T time-series observations.When T increases, the informational content of the prior, $g\left(a_i | \delta \right)$, vanishes, and its contributions to the posterior distribution becomes negligible with respect to the log-likelihood.

A similar argument can be made for σ_a^2 based on two considerations. On the one hand, Lancaster (2004) shows that assuming a flat uniform prior for $v_i = \ln\left(a_i \right)$, and integrating out a_i leads to a posterior for β which is proportional to the conditional likelihood

[1] see, among others, Wooldridge (2010b)

characterizing the Poisson FE estimator. On the other hand, the ML estimate of the δ hyperparameter characterizing the Gamma prior of the Poisson RE estimator minimizes the Kullback-Leibler distance between the postulated distribution and the population distribution of the individual effects (White, 1982). It seems plausible, then, to expect that increasing values of σ_a^2 in the process generating the data would make the prior progressively flatter. The uniform prior that leads to the FE estimator of β is the limiting case that one would obtain using the conjugate proper Gamma prior when its precision goes to zero (Lancaster, 2004).[2]

The objective of the Monte Carlo study, which will be illustrated in the next section, is to understand the extent to which this result is likely to apply in common panel data where both T and σ_a^2 are finite.

One important caveat to bear in mind concerns the applicability of the algebraic result introduced above to the case of unbalanced panels, which is not considered in this study. When the number of time periods available differ between individuals, the first order conditions for the two estimators can be re-written as:

$$\sum_{i=1}^{N}\sum_{t=1}^{T_i}\mathbf{x}_{it}\left(y_{it}-\frac{\bar{y}_i}{\bar{\lambda}_i}\lambda_{it}\right)=\mathbf{0} \tag{3.12}$$

$$\sum_{i=1}^{N}\sum_{t=1}^{Ti}\mathbf{x}_{it}\left(y_{it}-\lambda_{it}\frac{\bar{y}_i-\delta/T_i}{\bar{\lambda}_i-\delta/T_i}\right)=\mathbf{0} \tag{3.13}$$

where T_i is the number of observations available for individual i, and both $\bar{y}_i$ and $\bar{\lambda}_i$are computed using the relevant number of observations. In this case the ratio δ/T_i becomes individual-specific, and possibly non-trivial for a fraction of individuals for which few time periods are available.

Intuitively, the applicability of the results presented in this study will depend on how small are the problematicT_i compared to the values of T considered in the simulations. More

[2]Notice that a similar argument for both T and σ_a^2 can be made in the linear case when the individual effects are assumed to follow a Normal distribution

importantly, it will depend on the weight of these observations in the composition of the sample. Since FOC are expressed as a sum over i, the higher is the fraction of cross-sectional units with small values of T_i, the higher is their weight in the sum, hence the divergence between the FOC of the two estimators.

A further complication arises when data are not randomly missing. In this latter case both Poisson FE and Poisson RE estimators need to be adjusted to take into account of sample selection. A more rigorous treatment of unbalanced panels, with missing at random and missing not at random, is left for future work.

3.2 Experimental design

The Monte Carlo study comprises six different data generating processes. They share a common structure which builds on Greene (2004) and Blundell et al. (2002). In all the considered DGP's the Poisson RE estimator is biased and inconsistent for the parameters of the conditional mean, due to a non-zero correlation between unobserved heterogeneity and the covariates.

Importantly, in order to investigate how close are the results obtained using the two estimators under different values of T and σ_a^2, each of the six DGP's is simulated using: i) six values of T: 2, 4, 6, 8, 10, 20; ii) four values of σ_a^2: 0.1, 0.5, 1, 2.

While Greene (2004) and Blundell et al. (2002) consider a maximum number of time periods equal to 8 in their simulations, all the experiments in this study also include the case $T = 20$. Given that common panel data applications make use of longitudinal studies spanning more than 8 years (see PSID 48 years , GSOEP 34 years , BHPS 18 years, to cite some of the most commonly used in the applied literature), choosing a maximum value of 20 time periods should provide a better picture of what practitioners are likely to find in practice. Moreover, given the identified patterns are all monotonic in T, the results will provide a clear indication of what is likely to happen in those cases in which more the panel length exceeds 20 time periods.

Contrary to the case of T, there is no a priori empirical guidance for the values of σ_a^2 that guarantees practical applicability of the results. The true distribution of unobserved heterogeneity is, indeed, unknown to the practitioner. Although some insights about the empirical distribution of the unobserved heterogeneity could be gained, in principle, by examining the distribution of the estimated fixed effects, or through the estimated σ_a^2 obtained using the random effect estimator, these methods can be potentially misleading. The estimated individual effects are inconsistent unless $T \to \infty$, and the estimated σ_a^2 is obtained under the assumption of a Gamma distribution for the unobserved heterogeneity. Following Blundell et al. (2002), I start by setting $\sigma_a^2 = 0.5$. After experimentation with each DGP the remaining values are chosen in order to strike a balance between providing enough variability in the ratio $1/\sigma_a^2 T$, and avoiding extreme values of the variance-to-mean ratio for Poisson distributed outcomes. The issue of practical applicability of the results with respect to the parameter σ_a^2 will be further discussed later in the paper when the results of the experiments are presented.

Large-N asymptotic properties of the two estimators are well-established in the literature, and are not the focus of the simulation study in this paper. For this reason, N is kept fixed and equal to 1,000 in all the DGP's (this is the maximum value considered in Blundell et al. 2002) . Having a large number of cross-section units is also a common feature of panel data in which N is typically large, and T is fixed and small relative to N.

Combining the different values of T and σ_a^2, I obtain 24 sub-DGP's for each of the data generating processes considered. As in Blundell et al. (2002), all the results presented in this study are based on 1000 replications. In each replica, after generating the data according to the relevant DGP, the model is estimated using the two estimators.

Since regression models often include a mix of continuous and dummy variables, this feature is replicated in the experiments. In particular, all the considered DGP's, the set of explanatory variables comprises one time-varying continuous variable, c_{it}, one time-varying dummy variable, $d1_{it}$, and one time-constant dummy variable $d2_i$. Each of the three explanatory variables is correlated with unobserved heterogeneity. The choice not to include a time-constant continuous variable is driven by the fact that this type of variables are not frequently encountered in common panel data applications (a notable exception is the inclusion of distance in gravity models commonly estimates using Poisson regressions). It is worth to notice, however, that some differences exist in terms of the the bias of the RE estimator for the coefficient on the time-constant variable, when data are simulated using a continuous variable. A more detailed discussion of this issue is provided section (3.3).

3.2.1 DGP 1 - the benchmark case

Table 3.1 summarizes the characteristics of DGP 1, and provides a description of the generic structure of the data generating processes used throughout the Monte Carlo experiment.

The first element randomly drawn in each of the 1000 replications is a_i, a time-constant variable, representing unobserved heterogeneity. In all DGP's, except DGP 2, a_i is drawn from a $Gamma\left(\delta, \frac{1}{\delta}\right)$ distribution.

The time-varying continuous variable c_{it}, is then generated using an auto-regressive process similar to Blundell et al. (2002). The variable is correlated with a_i through the τ parameter. The correlation is roughly equal to 0.5. The idiosyncratic component ε_{it} follows a Normal distribution with zero mean and variance equal to a fraction of the unobserved heterogeneity variance. UnlikeBlundell et al. (2002), this is done to keep the correlation between c_{it} and a_i fixed when increasing the variance of unobserved heterogeneity throughout the experiment (as previously explained this does not apply to the time-constant dummy variable $d2_i$).

The time-varying dummy $d1_{it}$, and the time-constant dummy $d2_i$, are subsequently generated using a latent representation. More specifically, two continuous variable, $l1_{it}$ and $l2_i$, are generated at first as described in the table. The two latent variables are correlated with a_i both directly, and indirectly through, respectively, c_{it} and $\bar{c}_i$. The two dummies, $d1_{it}$ and $d2_i$, take then a value of 1 when the respective latent variables are below the 40th percentile, and 0 otherwise. Correlation between $d1_{it}$ and a_i, and between $d2_i$ and a_i, is about 0.35. The choice

The outcome variable y_{it} is generated as a random draw from a Poisson distribution with parameter λ_{it} depending on c_{it}, $d1_{it}$, $d2_i$, and a_i.

The values for true coefficients on c_{it}, $d1_{it}$, and $d2_i$ are all set equal to 0.5. Experimentation with the data suggests that the results of the simulations are invariant to such choice. The chosen parameters imply a semi-elasticity of 0.5 for c_{it} (as in Blundell et al. (2002)), and a proportionate change of 65% for $d1_{it}$, and $d2_i$.

Table 3.1: DGP 1 description

$$
\begin{aligned}
y_{it} &\sim Poisson(\lambda_{it}) \\
\lambda_{it} &= \exp(\alpha + \beta_c c_{it} + \beta_{d1} d1_{it} + \beta_{d2} d2_i)\, a_i \\
&\quad \alpha = \beta_c = \beta_{d1} = \beta_{d2} = 0.5 \\
a_i &\sim Gamma\left(\delta, \frac{1}{\delta}\right); \quad \delta = \frac{1}{\sigma_a^2} \\
c_{it} &= \rho c_{it-1} + \tau a_i + \varepsilon_{it} \\
&\quad c_{i0} = \frac{\tau}{1-\rho} a_i + \varphi_i \\
&\quad \varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right); \quad \sigma_\varepsilon^2 = \kappa_c \sigma_a^2; \\
&\quad \varphi_i \sim N\left(0, \frac{\sigma_\varepsilon^2}{1-\rho^2}\right) \\
&\quad \rho = 0.5;\ \kappa_c = 0.5 \\
d1_{it} &= 1\left[l1_{it} \le l1_{p40}\right]; \quad l1_{p40}: Pr\left(l1_{it} \le l1_{p40}\right) = 0.4 \\
&\quad l1_{it} = \gamma_{l1}^c c_{it} + \gamma_{l1}^a a_i + \nu_{it} \\
&\quad \nu_{it} \sim N\left(0, \sigma_\nu^2\right); \quad \sigma_\nu^2 = \kappa_{l1} \sigma_a^2 \\
&\quad \gamma_{l1}^c = -0.5;\ \gamma_{l1}^a = -0.5;\ \kappa_{l1} = 0.5 \\
d2_i &= 1\left[l2_i \le p_4\right] \\
&\quad l2_i = \gamma_{l2}^c \bar{c}_i + \gamma_{l2}^a a_i + \xi_i \\
&\quad \xi_i \sim N\left(0, \sigma_\xi^2\right); \quad \sigma_\xi^2 = \kappa_{l2} \sigma_a^2 \\
&\quad \gamma_{l2}^c = -0.5; \gamma_{l2}^a = -0.5;\ \kappa_{l2} = 0.5
\end{aligned}
$$

.

3.2.2 DGP 2 - violation of the Gamma assumption

The RE estimator assumes that unobserved heterogeneity is uncorrelated with the other covariates in the conditional mean, and that it is Gamma-distributed. In DGP 2 the latter assumption is violated, and a log-normal distribution is used instead, so that $\ln(a_i) \sim N\left(0, \sigma_a^2\right)$. In this case the integral in equation (3.7) does not have a closed form solution.

Although estimates could be obtained using numerical integration, the model is estimated using the "standard" Poisson RE estimator which is, then, misspecified for the distribution of unobserved heterogeneity. The remaining characteristics of the DGP are identical to the one described in table 3.1.

3.2.3 DGP 3/4 - violation of the conditional serial independence assumption

Assuming that y_{it}, y_{ir} are independent conditional on $\mathbf{x}_i$ and a_i for all $r \neq t$, enables the second equality in equation (3.7). This assumption is violated in DGP 3 and DGP 4. In order to allow for correctly specified, but conditionally serially correlated marginal distributions, after generating the variables embedded in λ_{it}, the outcome y is generated using a Gaussian copula, as in Kwak (2011). Using a copula to simulate departures from the conditional serial independence assumption is computationally convenient since it requires to specify the marginal distribution for each variable and and the intended dependence among marginal distributions separately.

At first a multivariate vector is drawn from:

$$n = \begin{bmatrix} n_1 & n_2 & \ldots & n_T \end{bmatrix} \backsim N_T(\mu, \Sigma)$$

where:

$$\mu = \begin{bmatrix} 0 & 0 & \ldots & 0 \end{bmatrix}$$

$$\Sigma = \begin{pmatrix} 1 & \rho_y & \cdots & \rho_y^{T-1} \\ \rho_y & 1 & \cdots & \rho_y^{T-2} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_y^{T-1} & \rho_y^{T-2} & \ldots & 1 \end{pmatrix}$$

The parameter ρ, which determines the degree of persistence in the process, is set equal to

0.5 in DGP 3, and 0.9 in DGP 4. This allows us to investigate the consequences of a less and more severe misspecification.

The multivariate normal implicitly defines a Gaussian copula:

$$\Phi(n_1, n_2, \ldots, n_T) = C(\Phi_1(n_1), \Phi_2(n_2), \ldots, \Phi_T(n_T))$$

In order to generate a Poisson multivariate vector with the same dependence structure, the generic uniformly-distributed marginal CDF $\Phi_t(n_t)$ is transformed using the inverse CDF. Given the discrete nature of the Poisson distribution, an algorithm is used to obtain the inverse CDF based on the definition of the CDF inverse: $F^{-1}(\Phi_t(n_t)) = \inf\{y \in \mathbb{R} : F(y) \geq \Phi_t(n_t)\}$. The algorithm is similar to the one described in Trivedi et al. (2007).

Given the presence of other covariates, and especially time-invariant heterogeneity, in the process generating y, its dependence structure need not coincide with the one imposed by the copula. In order to check whether the algorithm produces the desired structure of dependence, pairwise correlation coefficients are calculated for the residual-like quantities $q_{it} = y_{it} - \lambda_{it}$, rather than the original outcome. Table 3.2 compares the pairwise correlations between n_{it} and n_{it+k}, with the one between q_{it} and q_{it+k} for the case $T = 10$, and $\sigma_a^2 = 1$, as an illustrative example. The table shows the average pairwise correlations over 1000 replications, separately for $\rho = 0.5$ and $\rho = 0.9$.

Table 3.2: Average pairwise correlation of the original joint normals n_{it} and $q_{it} = y_{it} - \lambda_{it}$

		n_1/q_1	n_2/q_2	n_3/q_3	n_4/q_4	n_5/q_5	n_6/q_6	n_7/q_7	n_8/q_8	n_9/q_9	n_{10}/q_{10}
$\rho = 0.5$	n_1	1	0.500	0.250	0.125	0.062	0.031	0.016	0.008	0.002	0.001
	q_1	1	0.472	0.232	0.114	0.057	0.029	0.016	0.007	0.002	-0.002
$\rho = 0.9$	n_1	1	0.900	0.810	0.729	0.656	0.591	0.531	0.478	0.430	0.387
	q_1	1	0.859	0.762	0.681	0.610	0.548	0.493	0.444	0.397	0.357

Notes: the table compares the pairwise correlations between n_{it} and n_{it+k}, with the one between q_{it} and q_{it+k}. The results shown are the average correlations over 1000 replications of DGP 3 ($\rho = 0.5$) and DGP 4 ($\rho = 0.9$) for the case T=10, and $\sigma_a^2 = 1$.

3.2.4 DGP 5 - violation of the Poisson assumption

In DGP 5 the outcome y_{it} is generated from an $Exponential(\lambda_{it})$ distribution, where

$$\lambda_{it} = \frac{1}{\exp\left(\alpha + \beta_c c_{it} + \beta_{d1} d1_{it} + \beta_{d2} d2_i\right) a_i}$$

$$a_i \sim Gamma\left(\delta, \frac{1}{\delta}\right)$$

The above parametrization guarantees that

$$E\left[y_{it}|\mathbf{x}_{it}, a_i\right] = 1/\lambda_{it} = \exp\left(\alpha + \beta_c c_{it} + \beta_{d1} d1_{it} + \beta_{d2} d2_i\right) a_i$$

Given the adopted parametrization results in an exponential conditional mean, the Poisson FE estimator retains consistency, although inference should be based on corrected standard errors to take into account the failure of the equidispersion assumption ($E\left[y_{it}|\mathbf{x}_{it}, a_i\right] \neq V\left[y_{it}|\mathbf{x}_{it}, a_i\right]$). However, the Poisson assumption ($y_{it} \sim Poisson(\lambda_{it})$) made to obtain the RE estimator is not valid, making the estimator misspecified for the distribution of the outcome.

3.2.5 DGP 6 - violation of the conditional mean assumption

Finally, DGP 6 is designed to make the estimators both biased and inconsistent for the true parameters of the conditional mean. In order to do so, the outcome is generated by a Tobit model. The following table summarizes the characteristics of the DGP.

Table 3.3: Description of DGP 6

y_{it}	$=$	$1[z_{it} > 0] z_{it}$
z_{it}	$=$	$\alpha^t + \beta_c^t c_{it} + \beta_{d1}^t d1_{it} + \beta_{d2}^t d2_i + \ln a_i + \omega_{it}$
		$\omega_{it} \sim N(0, 10)$
		$\alpha^{tob} = 2.5;\ \beta_c^{tob} = \beta_{d1}^{tob} = \beta_{d2}^{tob} = 0.5$
a_i	$\sim$	$Gamma\left(\delta, \frac{1}{\delta}\right);\ \delta = \frac{1}{\sigma_a^2}$
c_{it}, $d1_{it}$, $d2_i$ generated as in DGP 1, but $\ln a_i$ used instead of a_i		

Given the difference between the true conditional mean and the one underlying the considered estimators, true slope parameters cannot be compared to the estimated ones when assessing the magnitude of the bias. Average partial effects (APE's) could be used, in principle, for the task at hand. However, neither the FE nor the RE estimator allow to compute APE's as they generally depend on unobserved heterogeneity. One advantage of the exponential conditional mean parametrization is that the estimated parameters can be directly interpreted as semi-elasticities (for continuous variables) and proportionate changes (for dummy variables using the expression $\exp(\beta_j) - 1$) . Focusing on the latter could be, then, a valuable practitioner-oriented alternative. The main drawback of this approach is that these quantities are not constant in a Tobit model, but depend on the values of covariates and unobserved heterogeneity. In order to compute their "true value", I adapt the concept of average partial effects to semi-elasticities and proportionate changes. The expression for the semi-elasticity of y_{it} with respect to c_{it} can be written as:

$$\frac{\partial E[y_{it}|\mathbf{x}_{it}, a_i]}{\partial c_{it}} \times \frac{1}{E[y_{it}|\mathbf{x}_{it}, a_i]}$$

In the Tobit model it can be shown that:

$$E[y_{it}|\mathbf{x}_{it}, a_i] = \Phi\left(\frac{\mathbf{x}_{it}'\beta}{\sigma}\right)\mathbf{x}_{it}'\beta_c + \sigma\phi\left(\frac{\mathbf{x}_{it}'\beta}{\sigma}\right)$$

The partial effect of the continuous variable c_{it} is, then, equal to:

$$\frac{\partial E\left[y_{it}|\mathbf{x}_{it},a_i\right]}{\partial c_{it}}=\beta_c\Phi\left(\frac{\mathbf{x}_{it}'\beta}{\sigma}\right)$$

while the partial effect of the dummy variable dj_{it} is equal to the difference:

$$E\left[y_{it}|\mathbf{x}_{it},a_i,dj_{it}=1\right]-E\left[y_{it}|\mathbf{x}_{it},a_i,dj_{it}=0\right]$$

For the continuous variable c_{it}, the value of the partial effect, and of the conditional mean, is first computed for each panel unit and time periods using a single replica of the experiment with $N = 1,000,000$. The "true average semi-elasticity" is, then, computed according to:

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\frac{\partial E\left[y_{it}|\mathbf{x}_{it},a_i\right]}{\partial c_{it}}\times\frac{1}{E\left[y_{it}|\mathbf{x}_{it},a_i\right]}\right)$$

For the two dummy variables $d1_{it}$ and $d2_i$, the "true average proportionate change" due to the dummy switching form 0 to 1 is computed as:

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\frac{E\left[y_{it}|\mathbf{x}_{it},a_i,dj_{it}=1\right]-E\left[y_{it}|\mathbf{x}_{it},a_i,dj_{it}=0\right]}{E\left[y_{it}|\mathbf{x}_{it},a_i,dj_{it}=0\right]}\right)$$

3.3 Results

Table 3.4 below presents the results of the Monte Carlo study for the benchmark case DGP 1. The tables shows, separately for each combination of T and σ_a^2, the average bias and the standard deviation of the sampling distribution of each estimator. The average bias is computed according to[3]:

$$Bias_\beta=\frac{1}{R}\sum_{r=1}^{R}\left[\left(\hat{\beta}_r/\beta_0\right)-1\right];\;\; R=1000$$

[3]When DGP 6 is considered, the bias is computed according to $\frac{1}{R}\sum_{r=1}^{R}\left[\left(\left(\exp(\hat{\beta}_r)-1\right)/g(\mathrm{x}_{it},\beta_0,a_i\right)-1\right]$

The average value of the absolute difference $|\hat{\beta}^{FE} - \hat{\beta}^{RE}|$ is also presented for the coefficients of c_{it} and $d1_{it}$, the two time-varying variables.

To ease interpretation of the results, the average value of the absolute difference between the two estimators is also plotted against T, for each value of σ_a^2. The graphs are presented separately for c_{it} and $d1_{it}$, in figure 3.1 and 3.2 for the benchmark case. Finally, figure 3.3 shows the average bias of the estimated coefficient on the time-invariant dummy $d2_i$ obtained using the RE estimator.

The results in table 3.4 show that, as expected, the performance of the FE estimator is almost insensitive to variations in σ_a^2 and T. The sampling distribution of the estimator is always centered around the true values of the parameters β_c and β_{d1}. More importantly, the results confirm the role played by σ_a^2 and T in determining the performance of the RE estimator. The bias of the estimated coefficients of c_{it} and d_{it} obtained using the RE estimator decreases with increasing values of T and σ_a^2, as well as the distance between the estimated coefficients, as can be seen in figures 3.1 and 3.2.

Focusing on the continuous variable c_{it}, a visual inspection of the the plots in figure 3.1 shows that, while additional time periods makes the RE estimates move closer the ones obtained using the FE estimator (for any given level of σ_a^2), the distance between the two remains quite large when heterogeneity is heavily concentrated around its mean. As a result, the estimator exhibits a poor performance in this latter case. More specifically, from table 3.4, when $\sigma_a^2 = 0.1$, the RE estimator shows a substantial bias, equal to 17.5% of the true value, in the extreme case of $T = 20$. Things get better, in this respect, when flatter distributions of unobserved heterogeneity are considered. "Moderate" levels of σ_a^2 , i.e. $\sigma_a^2 = 0.5$ and $\sigma_a^2 = 1$, lead to the average bias falling below 5% if the number of time periods is higher than, respectively, 10 and 6. In the extreme case of $\sigma_a^2 = 2$, the bias of the RE is constantly below 10%, reaching a minimum of 0.3% of the true value when $T = 20$.

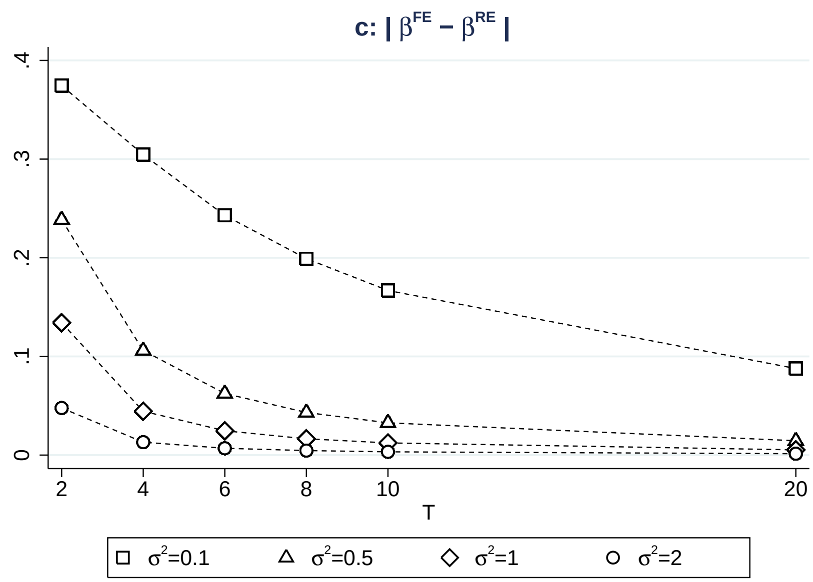

Figure 3.1: DGP 1 - c_{it}: time-varying continuous variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

Focusing on the time-varying dummy $d1_{it}$, the results in table 3.4 and the plots in Figure 3.2 show a pattern similar to the one discussed for c_{it}. Although a smaller distance between the estimates provided by the two estimators, and a consequently lower level of bias for the RE estimator, is observed in general, the distance is shown to be monotonically decreasing in T and σ_a^2. The better performance relative to the coefficient on c_{it} is likely to be due to the lower level of correlation between $d1_{it}$ and a_i. Indeed, while the correlation between $d1_{it}$ and unobserved heterogeneity is roughly constant and equal to 0.35, part of it is due to the correlation between $d1_{it}$ and c_{it}, which is accounted for in estimation.

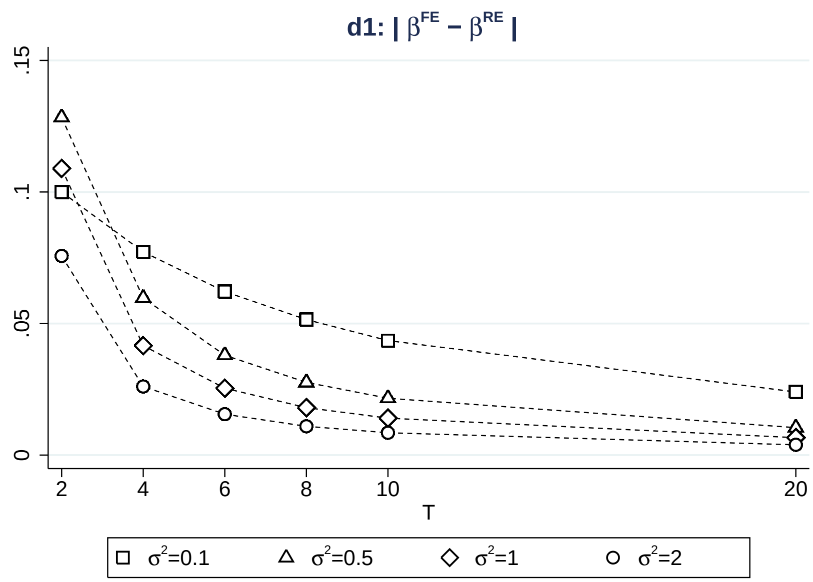

Figure 3.2: DGP 1 - $d1_{it}$: time-varying dummy variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

Finally, the results of the Monte Carlo experiment for the estimated coefficient on the time-constant $d2_i$ reveal that, differently from what is seen for the two time-varying variables, increasing values of T and σ_a^2 do not result in improved performance. The plots in figure 3.3 show that the bias of the estimated coefficient obtained using the RE estimator is substantial in all cases, and increasing in T and σ_a^2. This last result, however, should be interpreted with caution. A comparison with the linear case can provide some intuitions about these findings, given the striking similarities outlined in section 3.1. As described above, the RE estimator in the linear case is obtained as an OLS regression of $(y_{it} - \theta \bar{y}_i)$ on $(x_{it} - \theta \bar{x}_i)$. It can be shown that, when the RE assumption is violated, the RE estimate of β_j suffers an omitted variable bias, which can be expressed by:

$$\frac{\text{Cov}\left(\left(x_{j,it} - \theta \bar{x}_{j,i}\right), \left(a_i - \theta \bar{a}_i\right)\right)}{\text{V}\left(x_{j,it} - \theta \bar{x}_{j,i}\right)}$$

Whenx x_j is time-constant, this simplifies to:

$$\frac{\text{Cov}\left(x_{j,i}, a_i\right)}{\text{V}\left(x_{j,i}\right)}$$

The absence of within variation has two major implications. On the one hand, the bias in the RE estimates of β_j does not depend on θ, and hence does not depend on T or σ_a^2. On the other hand, the variance of the de-meaned variable tends to zero when θ converges to one, resulting in an identification problem.

When x_j is a dummy variable, as in all the considered DGP's, its total variance $\text{V}\left(x_{j,i}\right)$ is fixed at $p(1-p)$. However, if the variable is generated as described in section 3.2.1, its covariance with a_i is increases with increasing values of σ_a^2. This is due to the fact that the underlying latent variable is a linear function of a_i. Since $\text{V}\left(x_{j,i}\right)$ is fixed and cannot be re-scaled to take into account the increasing covariance, the omitted variable bias becomes an increasing function of σ_a^2.

Although the analogy with the linear case is not a formal proof of the reasons why these patterns are observed in the experiment, when data are simulated using a time-constant continuous variable, the resulting bias of the RE estimator is substantial but fixed for every level of T and σ_a^2.

The identification problem is also visible by examining the standard deviation of the sampling distribution of the estimator. Table 3.4 shows that, differently from the case of $d1_{it}$ and c_{it} where the efficiency gains associated with RE estimation tend to vanish, increasing values of σ_a^2 are associated with higher values of the empirical standard deviation of the estimated coefficient.

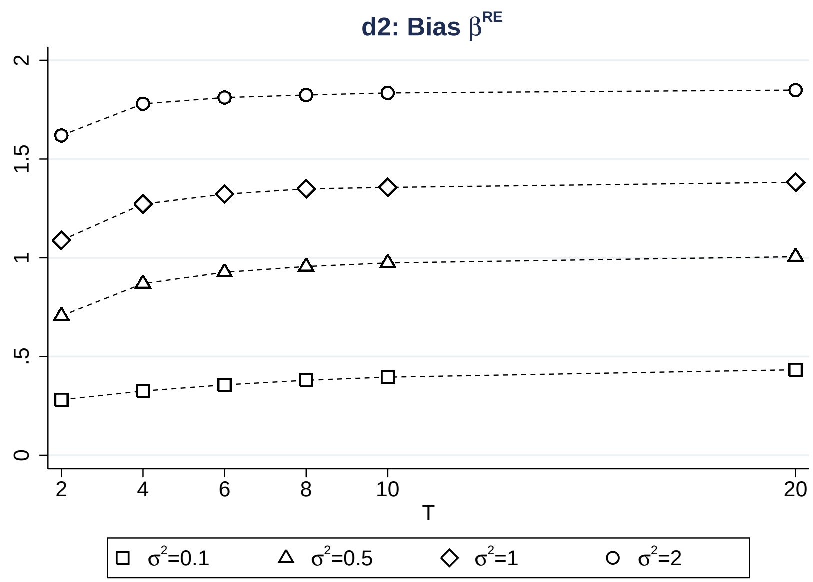

Figure 3.3: DGP 1 - $d2_i$: time-constant dummy variable. Mean value of the bias of the estimated coefficients from RE estimators (% of the true value)

Tables and graphs presented in appendix 3 show that the results presented for the benchmark case also hold for the alternative data generating processes. No significant deviations from the described patterns emerged when considering different types of misspecification of the RE estimator in DGP 2 to DGP 5, which reveals an overall robustness of the RE estimator. Finally, when the exponential conditional mean assumption is violated in DGP 6, making both estimators biased and inconsistent, the FE estimator is found to be the one with the highest average bias. In this case, however, increasing T and σ_a^2 makes the estimates obtained using the two estimators become closer. As a consequence, the performance of the RE estimator worsens and approaches that of the FE estimator. This "convergence at the bottom" is quite surprising and deserves some further investigation, although it might be related to the way data are generated.

Table 3.4: DGP 1 - Results from Monte Carlo experiment

		c_{it}					$d1_{it}$					$d2_i$	
		FE		RE			FE		RE			RE	
σ_a^2	T	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_c^{FE} - \hat{\beta}_c^{RE}\rvert$	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_{d1}^{FE} - \hat{\beta}_{d1}^{RE}\rvert$	bias (%)	SD
0.1	2	-0.007	0.090	0.742	0.049	0.375	0.001	0.036	0.200	0.028	0.100	0.281	0.030
	4	-0.010	0.046	0.600	0.036	0.305	0.001	0.021	0.156	0.019	0.077	0.325	0.023
	6	-0.000	0.033	0.486	0.030	0.243	-0.001	0.016	0.124	0.016	0.062	0.357	0.023
	8	0.000	0.028	0.398	0.026	0.199	0.001	0.014	0.104	0.014	0.052	0.380	0.021
	10	0.000	0.024	0.334	0.024	0.167	-0.000	0.012	0.087	0.012	0.044	0.396	0.020
	20	-0.001	0.016	0.175	0.016	0.088	0.000	0.009	0.048	0.009	0.024	0.433	0.019
0.5	2	0.000	0.038	0.478	0.029	0.239	-0.000	0.035	0.256	0.033	0.128	0.706	0.044
	4	-0.001	0.018	0.211	0.018	0.106	0.001	0.021	0.120	0.021	0.060	0.869	0.043
	6	0.000	0.014	0.125	0.014	0.062	0.001	0.015	0.077	0.015	0.038	0.927	0.043
	8	-0.001	0.011	0.086	0.011	0.043	-0.001	0.013	0.054	0.013	0.028	0.956	0.041
	10	-0.001	0.009	0.065	0.009	0.033	0.001	0.012	0.045	0.012	0.022	0.974	0.040
	20	0.000	0.006	0.029	0.006	0.015	-0.001	0.008	0.020	0.008	0.010	1.006	0.041
1	2	-0.000	0.023	0.268	0.024	0.134	-0.002	0.033	0.216	0.034	0.109	1.088	0.059
	4	0.001	0.011	0.090	0.012	0.044	0.002	0.019	0.085	0.020	0.042	1.272	0.058
	6	0.001	0.008	0.050	0.009	0.025	-0.003	0.015	0.048	0.015	0.025	1.322	0.057
	8	-0.000	0.007	0.033	0.007	0.017	-0.001	0.013	0.035	0.013	0.018	1.349	0.059
	10	-0.000	0.006	0.025	0.006	0.012	0.001	0.012	0.029	0.012	0.014	1.357	0.059
	20	-0.000	0.004	0.011	0.004	0.005	0.000	0.008	0.014	0.008	0.007	1.382	0.060
2	2	-0.001	0.012	0.095	0.016	0.048	-0.002	0.032	0.150	0.034	0.076	1.619	0.086
	4	-0.000	0.007	0.026	0.007	0.013	0.000	0.019	0.052	0.019	0.026	1.780	0.083
	6	-0.000	0.004	0.014	0.005	0.007	0.001	0.015	0.032	0.015	0.016	1.811	0.081
	8	-0.000	0.004	0.009	0.004	0.005	-0.001	0.012	0.021	0.012	0.011	1.824	0.080
	10	0.000	0.003	0.007	0.003	0.003	-0.000	0.011	0.017	0.011	0.008	1.835	0.080
	20	-0.000	0.002	0.003	0.002	0.001	0.000	0.007	0.008	0.007	0.004	1.849	0.081

Note: bias is calculated as percentage of the true value: $\frac{1}{R}\sum_{r=1}^{R}\left[\left(\hat{\beta}_r/\beta_0\right)-1\right]$; Number of replications $R = 1000$; Sample size for each replication $N = 1000$

3.4 Conclusions

The objective of this paper was to investigate to what extent the Poisson RE estimator is likely to produce results similar to ones obtained using the Poisson FE estimator when the random effects assumption is violated. The obvious advantage of the RE estimator is that it allows one to estimate the effect of time-invariant characteristics. The first order conditions of the Poisson RE estimator converge to the ones of the Poisson FE estimator when the number of time periods, T, or the variance of the time-constant unobserved heterogeneity, σ_a^2, tends to infinity. In order to evaluate the goodness of the approximation in common panel data situations, where both T and σ_a^2 are finite, I use a Monte Carlo study that includes six different data generating processes.

The result of the experiments confirm the role played by the number of time periods and the variance of the unobserved heterogeneity. The two estimators deliver very similar estimates of the coefficients of time-varying variables for reasonable values of T . The goodness of the approximation, however, crucially depends on σ_a^2, a characteristic of the distribution of unobserved heterogeneity that would be completely unknown to the practitioner.

The results for the time-constant dummy variable that included in all the data generating processes are less comforting. The estimated coefficient is shown to be severely biased for all choices of T and σ_a^2. Given that estimating the effect of time-constant characteristics is one of the main reasons why practitioners might prefer the RE estimator over the FE one, this result is an important cautionary note. The evidence provided suggests that for some reasonable values of T, the two estimators deliver very similar estimates of the coefficients on time-varying variables. In such cases the Hausman test may justify the use of the RE estimator if the interest is also on time-constant characteristics. If these characteristics are suspected to be correlated with unobserved heterogeneity, however, the results suggest that caution should be used when interpreting the associated coefficients.

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Appendix 1

Table A1.1: Duration model for job-to-job transitions - full estimates

	Waves 1-18		Waves 9-18	
Real monthly earnings (log)	-0.337***	-0.312***	-0.190**	-0.164*
	[0.057]	[0.058]	[0.087]	[0.088]
Hours: 1-15	-0.208	-0.092	-0.007	0.079
	[0.134]	[0.134]	[0.210]	[0.210]
Hours: 16-30	-0.091	-0.042	0.031	0.080
	[0.082]	[0.082]	[0.119]	[0.119]
Hours: 49 +	0.105*	0.113*	0.150	0.149
	[0.062]	[0.062]	[0.095]	[0.095]
Work at Night	0.176**	0.155**	0.137	0.099
	[0.071]	[0.071]	[0.102]	[0.102]
Rotating Shifts	0.097	0.075	0.010	-0.006
	[0.087]	[0.087]	[0.154]	[0.154]
Flexitime			0.069	0.070
			[0.099]	[0.099]
Other Flexible			0.056	0.058
			[0.162]	[0.161]
Job Satisfaction		-0.227***		-0.242***
		[0.014]		[0.022]
Female	-0.176***	-0.128**	-0.152*	-0.134*
	[0.056]	[0.057]	[0.081]	[0.081]
Age	-0.021	-0.035**	-0.059***	-0.070***
	[0.015]	[0.015]	[0.022]	[0.022]
Age^2	-0.000*	-0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Educ: Primary\Low. Sec.	-0.079	-0.043	-0.034	-0.012
	[0.072]	[0.072]	[0.112]	[0.112]
Educ: Higher	0.335***	0.301***	0.349***	0.315***
	[0.055]	[0.056]	[0.080]	[0.080]
Never married	0.014	-0.037	0.051	-0.005
	[0.069]	[0.069]	[0.104]	[0.104]
Separated	0.216***	0.207**	0.439***	0.410***
	[0.081]	[0.081]	[0.114]	[0.114]
Widowed	-0.126	-0.121	0.066	0.040
	[0.316]	[0.317]	[0.425]	[0.425]
Dependent Children	-0.113	-0.110	-0.057	-0.069
	[0.072]	[0.072]	[0.114]	[0.114]
Firm Size: <25	-0.069	-0.045	-0.146*	-0.117
	[0.057]	[0.057]	[0.084]	[0.084]
Firm Size: 100 - 499	-0.058	-0.078	-0.065	-0.080
	[0.064]	[0.064]	[0.094]	[0.094]
Firm Size: >500	-0.116	-0.136*	-0.147	-0.168

	Waves 1-18		Waves 9-18	
	[0.075]	[0.076]	[0.112]	[0.112]
Union at the Workplace	-0.389***	-0.404***	-0.391***	-0.406***
	[0.055]	[0.055]	[0.081]	[0.081]
Regional Dummies (17)	yes	yes	yes	yes
Industry Dummies (8)	yes	yes	yes	yes
Occupation Dummies (6)	yes	yes	yes	yes
Wave Dummies (17) (9)	yes	yes	yes	yes
Observations	33,959	33,959	16,092	16,092
Number of individuals	5,130	5,130	3,384	3,384
Number of spells	12,330	12,330	6,184	6,184

Notes: S.E. in brackets; *** p<0.01, ** p<0.05, * p<0.1.

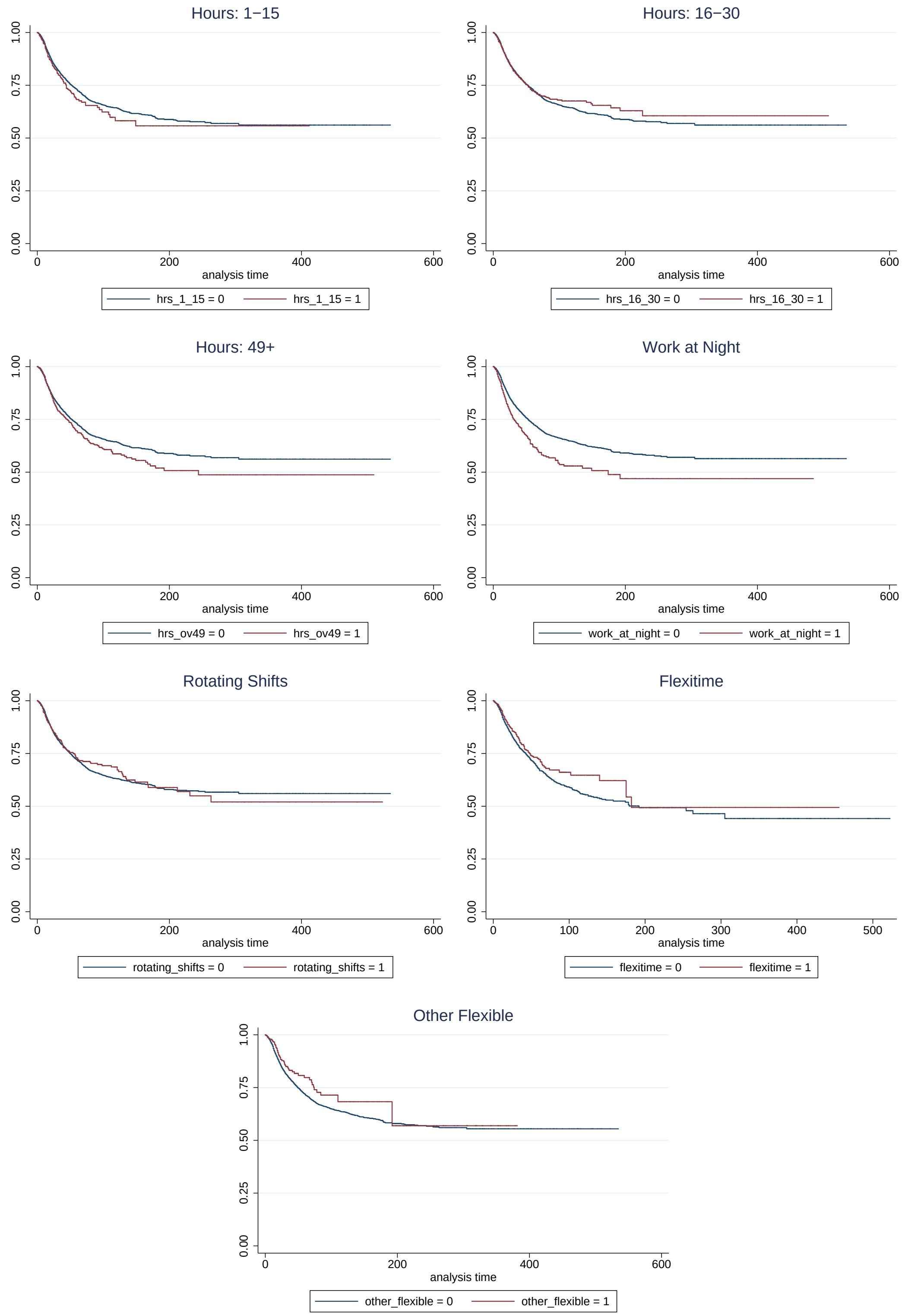

Figure A1.1: Kaplan-Meier estimates of the survivor function by job attributes of interest

Table A1.2: Job satisfaction - full estimates

	OLS FE		**Pooled Ordered Logit**		**BUC**	
	Waves 1-18	**Waves 9-18**	**Waves 1-18**	**Waves 9-18**	**Waves 1-18**	**Waves 9-18**
Real monthly earnings (log)	0.169***	0.190***	0.136***	0.107*	0.328***	0.406***
	[0.033]	[0.052]	[0.045]	[0.061]	[0.064]	[0.111]
Hours: 1-15	0.350***	0.258**	0.809***	0.663***	0.688***	0.538**
	[0.065]	[0.101]	[0.105]	[0.146]	[0.136]	[0.217]
Hours: 16-30	0.194***	0.158***	0.361***	0.316***	0.367***	0.320***
	[0.039]	[0.056]	[0.061]	[0.079]	[0.077]	[0.123]
Hours: 49 +	-0.045	-0.060	0.032	-0.018	-0.084	-0.113
	[0.028]	[0.041]	[0.045]	[0.063]	[0.053]	[0.085]
Work at Night	-0.070**	-0.088*	-0.183***	-0.283***	-0.132*	-0.173
	[0.036]	[0.051]	[0.054]	[0.072]	[0.068]	[0.106]
Rotating Shifts	-0.115**	-0.224***	-0.090	-0.104	-0.198**	-0.473***
	[0.049]	[0.074]	[0.069]	[0.106]	[0.088]	[0.149]
Flexitime		0.053		0.026		0.109
		[0.038]		[0.064]		[0.084]
Other Flexible		-0.096**		-0.019		-0.220**
		[0.045]		[0.084]		[0.104]
Female			0.324***	0.238***		
			[0.048]	[0.061]		
Age	0.015	0.015	-0.089***	-0.071***	0.032	-0.103**
	[0.032]	[0.047]	[0.011]	[0.015]	[0.067]	[0.040]
Age²	0.000***	0.001**	0.001***	0.001***	0.001***	0.001**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Educ: Primary\Low. Sec.	0.004	-0.274	0.300***	0.153*	0.003	-0.330
	[0.138]	[0.527]	[0.065]	[0.092]	[0.240]	[0.763]
Educ: Higher	-0.066	-0.220	-0.142***	-0.139**	-0.124	-0.488
	[0.066]	[0.194]	[0.047]	[0.061]	[0.131]	[0.415]
Never married	-0.158***	-0.125*	-0.241***	-0.252***	-0.302***	-0.254
	[0.050]	[0.075]	[0.059]	[0.079]	[0.095]	[0.156]

	OLS FE		Pooled Ordered Logit		BUC	
	Waves 1-18	**Waves 9-18**	**Waves 1-18**	**Waves 9-18**	**Waves 1-18**	**Waves 9-18**
Separated	-0.019	-0.065	-0.048	-0.179**	-0.047	-0.140
	[0.049]	[0.070]	[0.064]	[0.087]	[0.093]	[0.146]
Widowed	-0.087	-0.073	-0.064	-0.223	-0.201	-0.227
	[0.130]	[0.140]	[0.158]	[0.176]	[0.290]	[0.447]
Dependent Children	0.012	-0.035	-0.015	-0.170**	0.035	-0.073
	[0.031]	[0.047]	[0.047]	[0.071]	[0.063]	[0.103]
Firm Size: <25	0.031	-0.030	0.198***	0.219***	0.054	-0.072
	[0.028]	[0.040]	[0.043]	[0.059]	[0.054]	[0.085]
Firm Size: 100 - 499	0.004	-0.067	-0.060	-0.039	0.006	-0.140
	[0.030]	[0.043]	[0.044]	[0.061]	[0.056]	[0.087]
Firm Size: >500	0.016	-0.067	-0.067	-0.043	0.031	-0.138
	[0.037]	[0.051]	[0.053]	[0.068]	[0.070]	[0.102]
Union at the Workplace	-0.015	-0.006	-0.138***	-0.126**	-0.030	-0.004
	[0.038]	[0.063]	[0.043]	[0.058]	[0.071]	[0.118]
Regional Dummies (17)	yes	yes	yes	yes	yes	yes
Industry Dummies (8)	yes	yes	yes	yes	yes	yes
Occupation Dummies (6)	yes	yes	yes	yes	yes	yes
Wave Dummies (17), (9)	yes	yes	yes	yes	yes	yes
Observations	33,959	16,092	33,959	16,092	87,870	31,882
Number of individuals	5,130	3,384	5,130	3,384	3,903	2,294

Notes: S.E. in brackets; *** p<0.01, ** p<0.05, * p<0.1; the different number of observations in the last two columns is due to: i)individuals with no change in the dependent variable across time do not contribute to the likelihood; ii) the estimation sample is obtained by expanding the original sample a number of times equal to the possible cut-offs

Table A1.3: MWP estimates using job satisfaction - alternative estimators

	Pooled Ordered Logit		**BUC**	
	MWP	**S.E.**	**MWP**	**S.E.**
Hours: 1-15	-0.997***	0.004	-0.877***	0.052
Hours: 16-30	-0.930***	0.055	-0.673***	0.083
Hours: 49+	-0.212	0.274	0.292	0.212
Work at Night	2.827	2.255	0.495	0.336
Rotating Shifts	0.931	1.028	0.831	0.519
Flexitime	-0.215	0.486	-0.234	0.168
Other Flexible	0.195	0.958	0.720	0.512

Notes: *** p<0.01, ** p<0.05, * p<0.1. MWP's are expressed as fraction of real mothly earnings. MWP's for each characteristic are obtained using coefficients from table A1.2, columns 3 and 5. MWP's for Flexitime and Other Flexible are obtained using coefficients from the same tatable, columns 4 and 6; Standard Errors are obtained using Delta Method

Appendix 2

Table A2.1: Temporary work and earnings

	Earnings	Earnings growth		Subj. Exp. Test
	$\ln(y_{it})$	$\Delta \ln y_{it,t+1}$	$\Delta \ln y_{it,t+2}$	$\Delta \ln y_{it,t+1}$
	FE OLS	FE OLS	FE OLS	FE OLS
	(1)	(2)	(3)	(4)
Temporary work	-0.3373***	0.1062***	0.1298***	
	[0.020]	[0.025]	[0.031]	
ER_{it}= "worse"				-0.0621***
				[0.014]
ER_{it} = "better"				0.0345***
				[0.010]
Age: <25	-0.3106***	0.0166	0.0787	0.0155
	[0.035]	[0.042]	[0.052]	[0.042]
Age: 25-34	-0.0863***	-0.0137	0.0024	-0.0148
	[0.016]	[0.018]	[0.023]	[0.018]
Age: 45-54	-0.0013	0.0371**	-0.0051	0.0347**
	[0.015]	[0.017]	[0.021]	[0.017]
Age: 55+	-0.0848***	0.0621**	0.0354	0.0600**
	[0.025]	[0.029]	[0.036]	[0.029]
Large empl. / high. manag.	0.0562***	0.0035	-0.0051	0.0041
	[0.019]	[0.021]	[0.025]	[0.021]
Higher professional	0.0052	-0.0002	0.0113	0.0018
	[0.019]	[0.022]	[0.026]	[0.022]
Intermediate	-0.0746***	0.0417**	0.0491**	0.0447**
	[0.016]	[0.018]	[0.022]	[0.018]
Lower superv./ tech.	-0.0985***	-0.0002	0.0155	0.0013
	[0.016]	[0.019]	[0.023]	[0.019]
Semi-routine	-0.1670***	0.0355*	0.0738***	0.0380*

	Earnings	Earnings growth		Subj. Exp. Test
	$\ln(y_{it})$	$\Delta \ln y_{it,t+1}$	$\Delta \ln y_{it,t+2}$	$\Delta \ln y_{it,t+1}$
	FE OLS	FE OLS	FE OLS	FE OLS
	(1)	(2)	(3)	(4)
	[0.017]	[0.020]	[0.025]	[0.020]
Routine	-0.2493***	0.0226	0.1346***	0.0240
	[0.019]	[0.022]	[0.027]	[0.022]
Unemployed	-0.4212***	-0.5681***	0.1462***	-0.5799***
	[0.029]	[0.039]	[0.048]	[0.039]
Inactive	-0.7797***	-0.3915***	0.3755***	-0.3979***
	[0.029]	[0.046]	[0.054]	[0.046]
Number of adults in HH	0.0187**	-0.0050	0.0169	-0.0047
	[0.009]	[0.010]	[0.013]	[0.010]
Number of dependent children in HH	-0.0125*	0.0081	0.0329***	0.0061
	[0.007]	[0.009]	[0.011]	[0.009]
Number of individuals in work in HH	0.0139	0.0057	0.0065	0.0044
	[0.009]	[0.010]	[0.013]	[0.010]
Industry dummies	(8)	(8)	(8)	(8)
Region dummies	(17)	(17)	(17)	(17)
Wave dummies	(17)	(16)	(15)	(16)
Constant	7.3102***	-0.0889	-0.2315**	-0.0900
	[0.069]	[0.083]	[0.103]	[0.083]
Observations	22,992	17,812	14,883	17,812
Units	3,589	3,317	2,798	3,317

Notes: S.E. in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A2.2: Temporary work and uncertainty

	Sq. Filt. Res. $\hat{v}_{it}^2$ OLS (1)	Prob. Fut. Unemp Spell $Pr(U_{it+1} = 1)$ FE OLS (LPM) (2)	FE Logit (3)
Temporary Work	0.3563***	0.0542***	1.1557***
	[0.080]	[0.009]	[0.276]
Age: <25	0.0187	0.0159	1.1870*
	[0.075]	[0.015]	[0.715]
Age: 25-34	-0.0275	0.0075	0.5721*
	[0.032]	[0.006]	[0.323]
Age: 45-54	-0.0132	0.0046	0.2099
	[0.027]	[0.006]	[0.288]
Age: 55+	-0.0422	0.0071	0.5608
	[0.035]	[0.010]	[0.483]
Large empl. / high. manag.	-0.0272**	-0.0029	-0.1179
	[0.013]	[0.007]	[0.393]
Higher professional	0.0057	-0.0042	-0.3915
	[0.023]	[0.008]	[0.460]
Intermediate	0.0403**	-0.0051	-0.2484
	[0.018]	[0.006]	[0.281]
Lower superv./ tech.	0.0402	-0.0185***	-0.8141***
	[0.025]	[0.006]	[0.286]
Semi-routine	0.0774***	-0.0329***	-1.2188***
	[0.020]	[0.007]	[0.313]
Routine	0.1190***	-0.0222***	-0.8219***
	[0.028]	[0.008]	[0.305]
Inactive	1.7196***	0.0530***	0.8466**
	[0.426]	[0.013]	[0.431]
Unemployed	1.2292***		
	[0.214]		
Number of adults in HH	0.0106	0.0057	0.2281
	[0.016]	[0.004]	[0.168]
Number of dependent children in HH	0.0112	-0.0024	-0.1175
	[0.013]	[0.003]	[0.146]
Number of individuals in work in HH	-0.0273	0.0030	0.0945
	[0.018]	[0.004]	[0.166]
Industry dummies	(8)	(8)	(8)
Region dummies	(17)	(17)	(17)
Wave dummies	(16)	(16)	(16)
Constant	0.0772*	0.0042	
	[0.045]	[0.012]	
Observations	17,812	17,320	2,472
Units	3,317	3,307	363

Table A2.3: Saving function: average monthly saving

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Head in Temporary Work	-0.1679**	-0.1676**	-0.0674	-0.0666	-0.1631**	-0.1516**	-0.0540
	[0.066]	[0.066]	[0.064]	[0.066]	[0.066]	[0.065]	[0.063]
Age: <25	-0.3625***	-0.4079***	-0.1702	-0.2477**	-0.3636***	-0.3660***	-0.2371*
	[0.117]	[0.142]	[0.109]	[0.110]	[0.116]	[0.116]	[0.135]
Age: 25-34	-0.0260	-0.0345	0.0033	0.0028	-0.0272	-0.0281	-0.0109
	[0.051]	[0.052]	[0.050]	[0.050]	[0.050]	[0.050]	[0.050]
Age: 45-54	-0.0188	-0.0190	-0.0350	-0.0242	-0.0234	-0.0053	-0.0253
	[0.041]	[0.041]	[0.039]	[0.040]	[0.041]	[0.041]	[0.039]
Age: 55+	-0.0386	-0.0408	-0.0125	-0.0252	-0.0526	-0.0090	0.0015
	[0.066]	[0.066]	[0.062]	[0.064]	[0.066]	[0.065]	[0.063]
Large empl. / high. manag.	0.0832**	0.0837**	0.0653*	0.0673*	0.0822**	0.0785**	0.0627*
	[0.038]	[0.037]	[0.037]	[0.037]	[0.038]	[0.037]	[0.036]
Higher professional	0.0001	0.0004	0.0220	0.0184	-0.0021	-0.0007	0.0194
	[0.050]	[0.049]	[0.046]	[0.048]	[0.049]	[0.048]	[0.045]
Intermediate	-0.0299	-0.0297	0.0084	-0.0036	-0.0306	-0.0296	0.0055
	[0.041]	[0.041]	[0.037]	[0.039]	[0.041]	[0.041]	[0.038]
Lower superv./ tech.	-0.0054	-0.0055	0.0344	0.0204	-0.0083	-0.0028	0.0318
	[0.042]	[0.042]	[0.041]	[0.042]	[0.042]	[0.042]	[0.041]
Semi-routine	-0.0925*	-0.0920*	-0.0216	-0.0359	-0.0931*	-0.0781	-0.0142
	[0.049]	[0.049]	[0.045]	[0.048]	[0.049]	[0.048]	[0.045]
Routine	-0.0456	-0.0451	0.0343	0.0253	-0.0481	-0.0398	0.0338
	[0.059]	[0.059]	[0.058]	[0.059]	[0.059]	[0.058]	[0.057]
Unemployed	-0.5244***	-0.5239***	-0.4016***	-0.4253***	-0.5264***	-0.3963**	-0.3039**
	[0.157]	[0.157]	[0.141]	[0.145]	[0.158]	[0.159]	[0.145]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inactive	-0.3822***	-0.3826***	-0.2332**	-0.2259**	-0.3849***	-0.3176***	-0.1968**
	[0.101]	[0.101]	[0.099]	[0.098]	[0.101]	[0.100]	[0.099]
Housing: owned outright	0.1662***	0.1653***	0.1852***	0.1837***	0.1682***	0.1637***	0.1811***
	[0.047]	[0.047]	[0.045]	[0.046]	[0.047]	[0.046]	[0.044]
Housing: local authority rented	0.1864	0.1854	0.2709**	0.2177*	0.1852	0.2183*	0.2891**
	[0.115]	[0.115]	[0.111]	[0.115]	[0.113]	[0.117]	[0.112]
Housing: rented	0.2200***	0.2192***	0.2747***	0.2239***	0.2150***	0.2122***	0.2595***
	[0.075]	[0.075]	[0.072]	[0.078]	[0.075]	[0.073]	[0.070]
Number of adults in HH	-0.1360***	-0.1360***	-0.1387***	-0.1462***	-0.1212***	-0.1201***	-0.1175***
	[0.032]	[0.032]	[0.031]	[0.031]	[0.032]	[0.031]	[0.030]
Number of dependent children in HH	-0.2169***	-0.2165***	-0.2114***	-0.2224***	-0.1939***	-0.1972***	-0.1834***
	[0.028]	[0.028]	[0.026]	[0.027]	[0.030]	[0.027]	[0.028]
Number of individuals in work in HH	0.1640***	0.1643***	0.1188***	0.1613***	0.1515***	0.1532***	0.1068***
	[0.030]	[0.030]	[0.030]	[0.030]	[0.031]	[0.029]	[0.029]
Industry dummies (8)	√	√	√	√	√	√	√
Region dummies (17)	√	√	√	√	√	√	√
Wave dummies (17)	√	√	√	√	√	√	√
Unemployment rate		0.0044					0.0049
		[0.008]					[0.008]
Log total household earnings			0.6419***				0.5950***
			[0.044]				[0.042]
Log head's earnings				0.3262***			
				[0.039]			
Benefit income dummy					-0.0759**		-0.0345
					[0.034]		[0.034]
Fin. Exp.: "worse"						0.0763***	0.0665**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
						[0.029]	[0.027]
Fin. Exp.: “better”						-0.0176	-0.0025
						[0.021]	[0.020]
Fin. Sit.: “quite/very difficult”						-0.6947***	-0.6100***
						[0.104]	[0.101]
Fin. Sit: “just getting by”						-0.4476***	-0.4036***
						[0.036]	[0.034]
Observations	20,023	20,023	20,023	20,023	20,023	20,023	20,023
Units	2,784	2,784	2,784	2,784	2,784	2,784	2,784

Notes: S.E. in brackets; *** p<0.01, ** p<0.05, * p<0.1

Table A2.4: Consumption function: CONS 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Head in Temporary Work	-0.0249	-0.0251	-0.0191	-0.0193	-0.0264*	-0.0242	-0.2301
	[0.016]	[0.016]	[0.015]	[0.015]	[0.016]	[0.016]	[0.015]
Age: <25	-0.1183***	-0.0977***	-0.1112***	-0.1134***	-0.1165***	-0.1172***	-0.0897***
	[0.028]	[0.034]	[0.028]	[0.028]	[0.028]	[0.028]	[0.034]
Age: 25-34	-0.0382***	-0.0342***	-0.0369***	-0.0368***	-0.0370***	-0.0381***	-0.0320***
	[0.011]	[0.012]	[0.011]	[0.011]	[0.011]	[0.011]	[0.012]
Age: 45-54	-0.0046	-0.0047	-0.0051	-0.0047	-0.0014	-0.0026	0.0003
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Age: 55+	-0.0796***	-0.0787***	-0.0776***	-0.0783***	-0.0714***	-0.0770***	-0.0655***
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
Large empl. / high. manag.	0.0039	0.0038	0.0029	0.0029	0.0041	0.0030	0.0021
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Higher professional	0.0057	0.0057	0.0058	0.0058	0.0065	0.0051	0.0059
	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]
Intermediate	-0.0040	-0.0040	-0.0027	-0.0028	-0.0036	-0.0041	-0.0023
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Lower superv./ tech.	-0.0021	-0.0020	-0.0003	-0.0004	-0.0016	-0.0019	0.0005
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Semi-routine	0.0063	0.0063	0.0092	0.0091	0.0064	0.0070	0.0100
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
Routine	-0.0014	-0.0015	0.0028	0.0026	-0.0015	-0.0004	0.0037
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
Unemployed	-0.0447**	-0.0447**	-0.0381*	-0.0377*	-0.0458**	-0.0316	-0.0264
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inactive	-0.0604***	-0.0606***	-0.0485**	-0.0475**	-0.0615***	-0.0526**	-0.0421*
	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]
Housing: owned outright	0.0117	0.0117	0.0139	0.0134	0.0111	0.0110	0.0128
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
Housing: local authority rented	-0.0369*	-0.0368*	-0.0321	-0.0339	-0.0375*	-0.0331	-0.0290
	[0.022]	[0.022]	[0.021]	[0.022]	[0.021]	[0.022]	[0.021]
Housing: rented	-0.0705***	-0.0702***	-0.0674***	-0.0688***	-0.0698***	-0.0705***	-0.0664***
	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]
Number of adults in HH	0.1494***	0.1493***	0.1498***	0.1491***	0.1435***	0.1506***	0.1446***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Number of dependent children in HH	0.1578***	0.1575***	0.1584***	0.1580***	0.1470***	0.1592***	0.1480***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Number of individuals in work in HH	0.0220***	0.0219***	0.0200***	0.0218***	0.0278***	0.0209***	0.0251***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Industry dummies (8)	√	√	√	√	√	√	√
Region dummies (17)	√	√	√	√	√	√	√
Wave dummies (17)	√	√	√	√	√	√	√
Unemployment rate		-0.0021					-0.0018
		[0.002]					[0.002]
Log total household earnings			0.0233***				0.0235***
			[0.008]				[0.008]
Log head's earnings				0.0168***			
				[0.006]			
Benefit income dummy					0.0455***		0.0489***
					[0.008]		[0.008]
Fin. Exp.: "worse"						0.0083	0.0080

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
						[0.007]	[0.007]
Fin. Exp.: “better”						-0.0169***	-0.0164***
						[0.005]	[0.005]
Fin. Sit.: “quite/very difficult”						-0.0514***	-0.0497***
						[0.012]	[0.012]
Fin. Sit: “just getting by”						-0.0211***	-0.0202***
						[0.006]	[0.006]
Constant	5.1713***	5.1769***	4.9945***	5.0474***	5.1520***	5.1858***	4.9908***
	[0.066]	[0.066]	[0.090]	[0.081]	[0.065]	[0.066]	[0.090]
Observations	22,992	22,992	22,992	22,992	22,992	22,992	22,992
Units	3,589	3,589	3,589	3,589	3,589	3,589	3,589

Notes: S.E. in brackets; *** p<0.01, ** p<0.05, * p<0.1

Table A2.5: Consumption function: CONS 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temporary Work	-0.0216	-0.0216	-0.0149	-0.0164	-0.0214	-0.0215	-0.0154
	[0.013]	[0.013]	[0.013]	[0.014]	[0.013]	[0.013]	[0.013]
Age: <25	-0.1212***	-0.1239***	-0.1137***	-0.1162***	-0.1213***	-0.1198***	-0.1173***
	[0.028]	[0.034]	[0.027]	[0.027]	[0.028]	[0.027]	[0.034]
Age: 25-34	-0.0317***	-0.0322***	-0.0300***	-0.0305***	-0.0317***	-0.0307***	-0.0298***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Age: 45-54	-0.0136	-0.0136	-0.0146	-0.0139	-0.0140	-0.0119	-0.0130
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Age: 55+	-0.0580***	-0.0580***	-0.0578***	-0.0578***	-0.0590***	-0.0555***	-0.0558***
	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]
Large empl. / high. manag.	0.0227**	0.0227**	0.0219*	0.0222*	0.0225**	0.0220*	0.0213*
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Higher professional	0.0186	0.0186	0.0189	0.0188	0.0185	0.0185	0.0188
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
Intermediate	-0.0094	-0.0094	-0.0080	-0.0083	-0.0095	-0.0098	-0.0085
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Lower superv./ tech.	-0.0068	-0.0068	-0.0052	-0.0055	-0.0068	-0.0069	-0.0055
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Semi-routine	-0.0197*	-0.0197*	-0.0170	-0.0176	-0.0197*	-0.0194*	-0.0169
	[0.012]	[0.012]	[0.011]	[0.011]	[0.012]	[0.011]	[0.011]
Routine	-0.0071	-0.0070	-0.0035	-0.0045	-0.0071	-0.0076	-0.0043
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Unemployed	-0.0092	-0.0093	-0.0030	-0.0042	-0.0090	0.0032	0.0085
	[0.027]	[0.027]	[0.027]	[0.027]	[0.027]	[0.027]	[0.026]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inactive	-0.0444**	-0.0444**	-0.0359*	-0.0364*	-0.0443**	-0.0360*	-0.0285
	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]
Housing: owned outright	-0.3839***	-0.3839***	-0.3814***	-0.3822***	-0.3838***	-0.3850***	-0.3827***
	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]
Housing: local authority rented	-0.0611***	-0.0611***	-0.0567**	-0.0592**	-0.0611***	-0.0556**	-0.0519**
	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]
Housing: rented	-0.0722***	-0.0722***	-0.0679**	-0.0703**	-0.0722***	-0.0706***	-0.0669**
	[0.027]	[0.027]	[0.027]	[0.027]	[0.027]	[0.027]	[0.027]
Number of adults in HH	0.1408***	0.1408***	0.1409***	0.1405***	0.1413***	0.1418***	0.1419***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Number of dependent children in HH	0.0673***	0.0673***	0.0677***	0.0672***	0.0683***	0.0681***	0.0688***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Number of individuals in work in HH	0.0632***	0.0632***	0.0615***	0.0632***	0.0626***	0.0624***	0.0606***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Industry dummies (8)	√	√	√	√	√	√	√
Region dummies (17)	√	√	√	√	√	√	√
Wave dummies (17)	√	√	√	√	√	√	√
Unemployment rate		0.0003					0.0004
		[0.002]					[0.002]
Log total household earnings			0.0261***				0.0239***
			[0.006]				[0.006]
Log head’s earnings				0.0157***			
				[0.005]			
Benefit income dummy					-0.0051		-0.0017
					[0.007]		[0.007]
Fin. Exp.: “worse”						0.0023	0.0017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
						[0.007]	[0.007]
Fin. Exp.: “better”						-0.0111**	-0.0105**
						[0.005]	[0.005]
Fin. Sit.: “quite/very difficult”						-0.0595***	-0.0573***
						[0.011]	[0.011]
Fin. Sit: “just getting by”						-0.0206***	-0.0187***
						[0.005]	[0.005]
Constant	6.3862***	6.3853***	6.1906***	6.2733***	6.3889***	6.4032***	6.2227***
	[0.074]	[0.074]	[0.086]	[0.082]	[0.074]	[0.074]	[0.087]
Observations	15,102	15,102	15,102	15,102	15,102	15,102	15,102
Units	3,015	3,015	3,015	3,015	3,015	3,015	3,015

Notes: S.E. in brackets; *** p<0.01, ** p<0.05, * p<0.1

Appendix 3

DGP 2

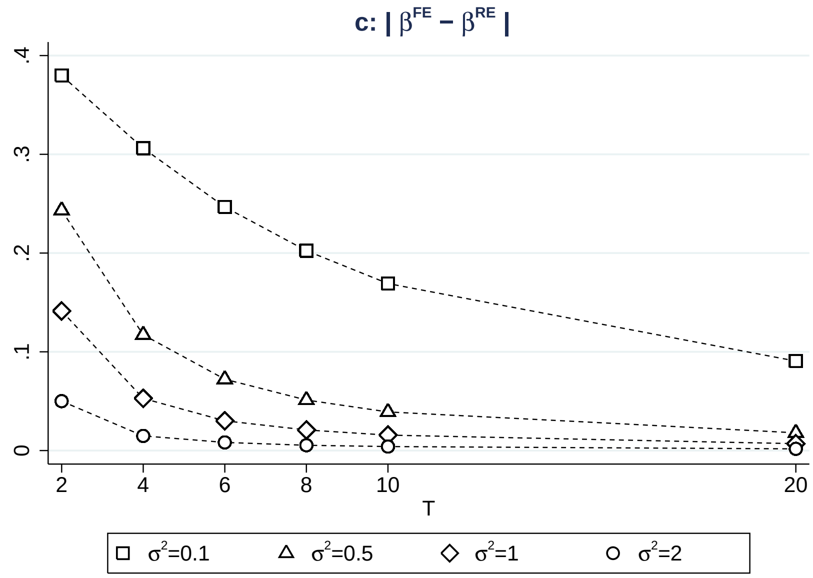

Figure A3.1: DGP 2 - c_{it} : time-varying continuous variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

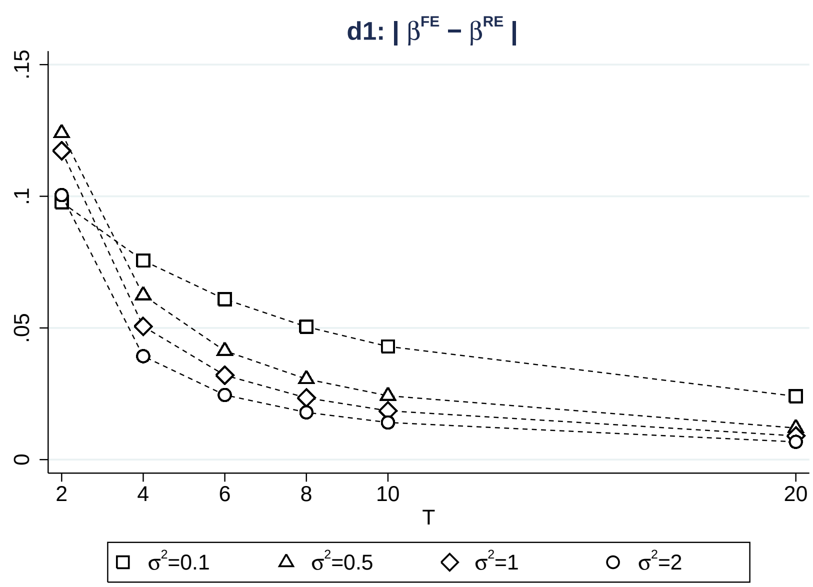

Figure A3.2: DGP 2 - $d1_{it}$: time-varying dummy variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

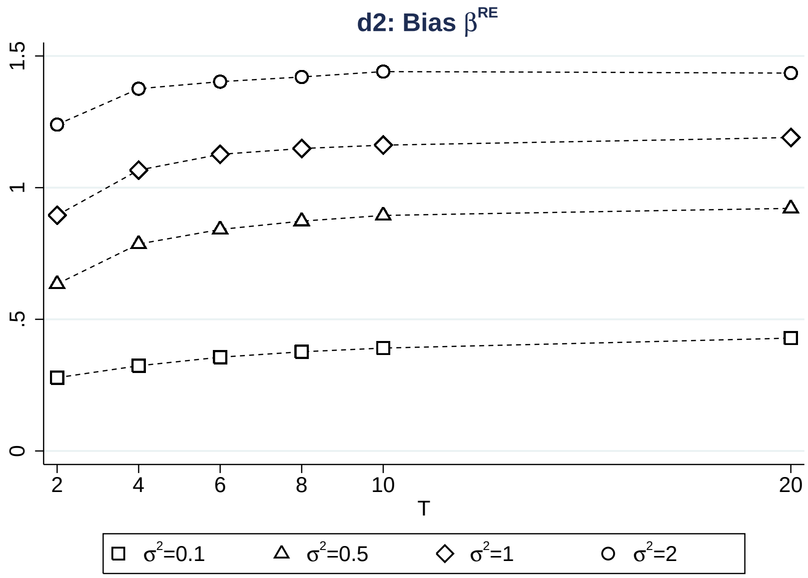

Figure A3.3: DGP 2 - $d2_i$: time-constant dummy variable. Mean value of the bias of the estimated coefficients from RE estimators (% of the true value)

Table A3.1: DGP 2 - Results from Monte Carlo experiment

		c_{it}					$d1_{it}$					$d2_i$	
		FE		RE			FE		RE			RE	
σ_a^2	T	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_c^{FE} - \hat{\beta}_c^{RE}\rvert$	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_{d1}^{FE} - \hat{\beta}_{d1}^{RE}\rvert$	bias (%)	SD
0.1	2	0.007	0.091	0.767	0.049	0.380	0.001	0.039	0.197	0.029	0.098	0.278	0.031
	4	0.004	0.044	0.616	0.036	0.306	-0.002	0.022	0.150	0.020	0.076	0.324	0.024
	6	0.003	0.034	0.496	0.031	0.247	0.002	0.016	0.124	0.016	0.061	0.356	0.022
	8	-0.002	0.028	0.403	0.027	0.202	0.001	0.014	0.102	0.014	0.050	0.377	0.021
	10	-0.000	0.024	0.338	0.024	0.169	0.000	0.013	0.086	0.013	0.043	0.391	0.020
	20	0.001	0.016	0.182	0.016	0.091	0.001	0.008	0.049	0.008	0.024	0.429	0.020
0.5	2	-0.002	0.036	0.485	0.027	0.243	0.005	0.038	0.253	0.035	0.124	0.634	0.044
	4	0.001	0.018	0.236	0.019	0.117	0.000	0.021	0.125	0.021	0.062	0.786	0.042
	6	0.001	0.013	0.145	0.014	0.072	-0.001	0.016	0.082	0.016	0.041	0.841	0.043
	8	-0.001	0.011	0.101	0.011	0.051	-0.001	0.014	0.061	0.014	0.031	0.873	0.041
	10	0.000	0.009	0.079	0.009	0.039	-0.001	0.012	0.048	0.012	0.024	0.894	0.042
	20	-0.000	0.006	0.036	0.006	0.018	-0.000	0.009	0.024	0.009	0.012	0.921	0.040
1	2	-0.001	0.022	0.282	0.031	0.141	-0.000	0.035	0.234	0.035	0.117	0.895	0.061
	4	0.001	0.010	0.107	0.015	0.053	-0.003	0.021	0.099	0.021	0.051	1.067	0.058
	6	0.000	0.008	0.060	0.010	0.030	-0.000	0.016	0.064	0.016	0.032	1.127	0.061
	8	0.001	0.006	0.042	0.007	0.021	0.001	0.013	0.048	0.013	0.023	1.149	0.058
	10	0.000	0.005	0.031	0.006	0.016	-0.000	0.012	0.037	0.012	0.019	1.161	0.057
	20	-0.000	0.004	0.014	0.004	0.007	0.001	0.008	0.019	0.008	0.009	1.190	0.057
2	2	0.001	0.011	0.101	0.028	0.050	0.003	0.033	0.204	0.034	0.100	1.239	0.089
	4	0.000	0.005	0.030	0.009	0.015	0.001	0.019	0.080	0.019	0.039	1.376	0.084
	6	0.000	0.004	0.017	0.006	0.008	0.000	0.015	0.049	0.015	0.025	1.403	0.082
	8	0.000	0.003	0.011	0.004	0.005	-0.000	0.013	0.036	0.013	0.018	1.420	0.080
	10	0.000	0.003	0.008	0.004	0.004	0.001	0.011	0.029	0.011	0.014	1.441	0.079
	20	-0.000	0.002	0.003	0.002	0.002	0.000	0.008	0.014	0.008	-0.007	1.435	0.077

Note: bias is calculated as percentage of the true value: $\frac{1}{R}\sum_{r=1}^{R}\left[\left(\hat{\beta}_r/\beta_0\right)-1\right]$; Number of replications $R = 1000$; Sample size for each replication $N = 1000$

DGP 3

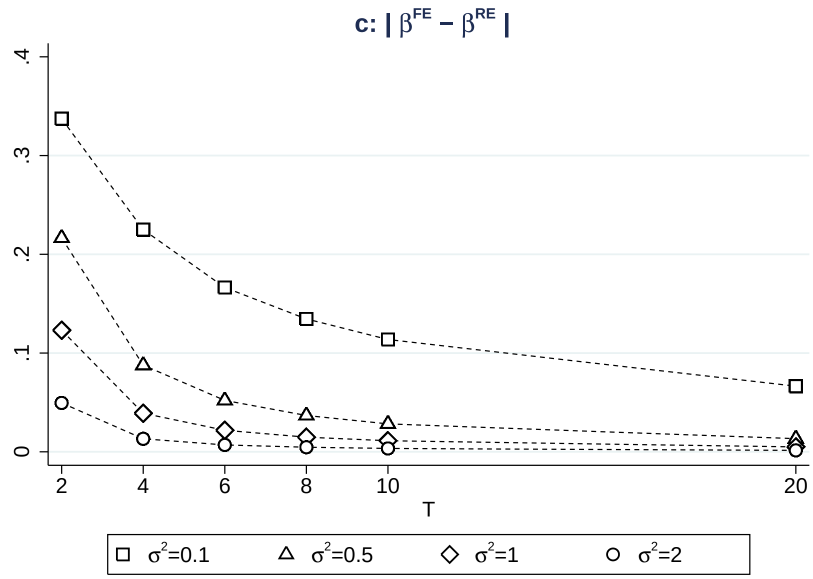

Figure A3.4: DGP 3 - c_{it}: time-varying continuous variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

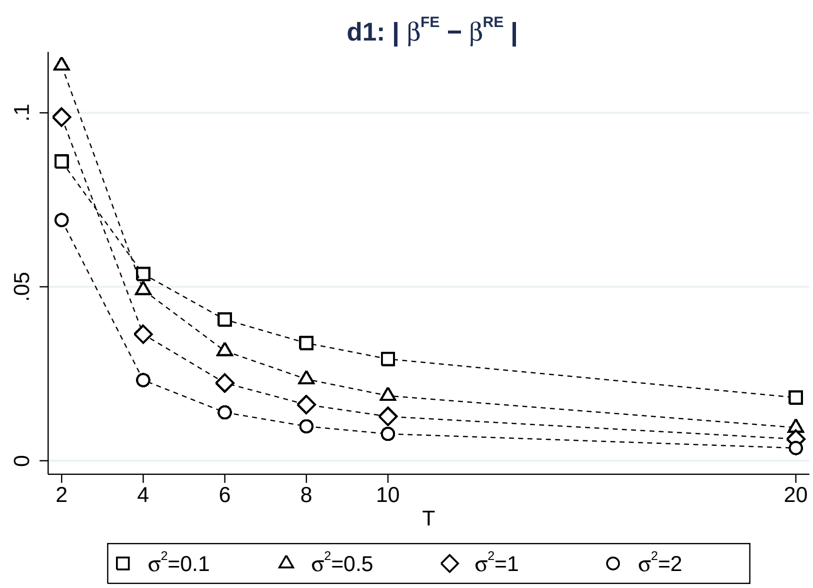

Figure A3.5: DGP 3 - $d1_{it}$: time-varying dummy variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

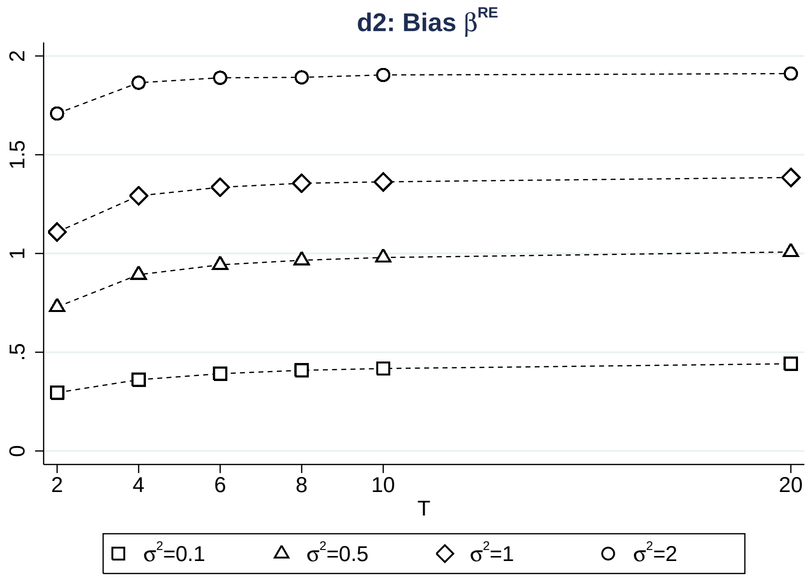

Figure A3.6: DGP 3 - $d2_i$: time-constant dummy variable. Mean value of the bias of the estimated coefficients from RE estimators (% of the true value)

Table A3.2: DGP 3 - Results from Monte Carlo experiment

		c_{it}					$d1_{it}$					$d2_i$	
		FE		RE			FE		RE			RE	
σ_a^2	T	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_c^{FE} - \hat{\beta}_c^{RE}\rvert$	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_{d1}^{FE} - \hat{\beta}_{d1}^{RE}\rvert$	bias (%)	SD
0.1	2	0.010	0.066	0.685	0.050	0.337	-0.000	0.027	0.172	0.025	0.086	0.295	0.034
	4	0.003	0.040	0.453	0.037	0.225	-0.002	0.018	0.105	0.018	0.054	0.361	0.029
	6	-0.003	0.032	0.330	0.031	0.166	-0.001	0.014	0.081	0.014	0.041	0.391	0.027
	8	-0.002	0.029	0.267	0.028	0.135	0.001	0.012	0.069	0.012	0.034	0.409	0.026
	10	0.003	0.025	0.230	0.025	0.114	-0.001	0.011	0.058	0.011	0.029	0.418	0.025
	20	0.001	0.018	0.134	0.018	0.066	-0.000	0.008	0.036	0.008	0.018	0.442	0.022
0.5	2	0.003	0.027	0.436	0.026	0.217	0.001	0.026	0.228	0.027	0.114	0.729	0.048
	4	0.001	0.017	0.176	0.017	0.088	0.001	0.016	0.100	0.016	0.049	0.893	0.045
	6	-0.001	0.013	0.104	0.013	0.052	0.001	0.014	0.064	0.015	0.032	0.942	0.046
	8	-0.001	0.011	0.073	0.011	0.037	0.001	0.012	0.048	0.013	0.023	0.966	0.044
	10	0.000	0.010	0.057	0.010	0.028	-0.000	0.011	0.037	0.011	0.019	0.980	0.042
	20	0.000	0.007	0.027	0.007	0.013	-0.000	0.008	0.019	0.008	0.010	1.008	0.042
1	2	-0.004	0.021	0.243	0.023	0.123	0.000	0.025	0.198	0.029	0.099	1.109	0.061
	4	-0.004	0.013	0.074	0.014	0.039	0.003	0.017	0.076	0.017	0.036	1.292	0.061
	6	-0.005	0.011	0.039	0.011	0.022	0.003	0.013	0.047	0.013	0.022	1.335	0.061
	8	-0.004	0.011	0.026	0.011	0.015	0.002	0.012	0.034	0.012	0.016	1.356	0.061
	10	-0.005	0.011	0.018	0.011	0.011	0.001	0.011	0.027	0.011	0.013	1.363	0.061
	20	-0.004	0.008	0.006	0.009	0.005	0.001	0.008	0.013	0.008	0.006	1.385	0.060
2	2	-0.089	0.047	0.010	0.048	0.050	0.017	0.027	0.156	0.028	0.069	1.709	0.107
	4	-0.092	0.037	-0.065	0.037	0.013	0.028	0.020	0.074	0.020	0.023	1.865	0.098
	6	-0.094	0.033	-0.080	0.034	0.007	0.033	0.018	0.061	0.018	0.014	1.890	0.094
	8	-0.090	0.032	-0.080	0.032	0.005	0.034	0.017	0.054	0.017	0.010	1.892	0.093
	10	-0.094	0.031	-0.087	0.031	0.003	0.037	0.017	0.053	0.017	0.008	1.904	0.091
	20	-0.094	0.027	-0.091	0.027	0.001	0.045	0.015	0.052	0.015	0.004	1.911	0.091

Note: bias is calculated as percentage of the true value: $\frac{1}{R}\sum_{r=1}^{R}\left[\left(\hat{\beta}_r/\beta_0\right)-1\right]$; Number of replications $R = 1000$; Sample size for each replication $N = 1000$

DGP 4

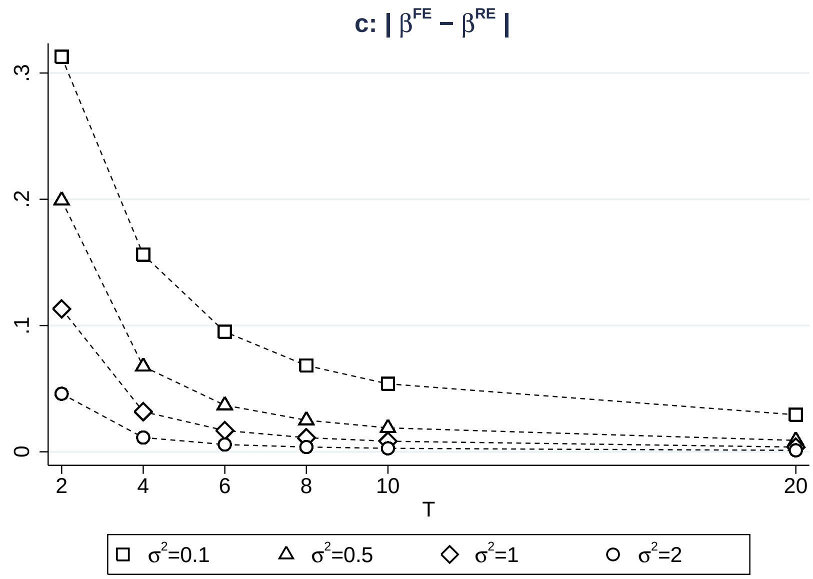

Figure A3.7: DGP 4 - c_{it}: time-varying continuous variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

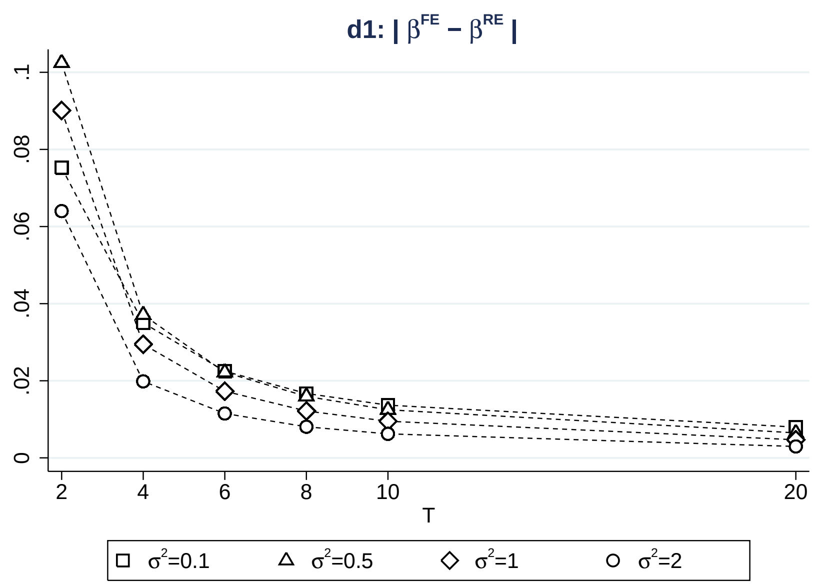

Figure A3.8: DGP 4 - $d1_{it}$: time-varying dummy variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

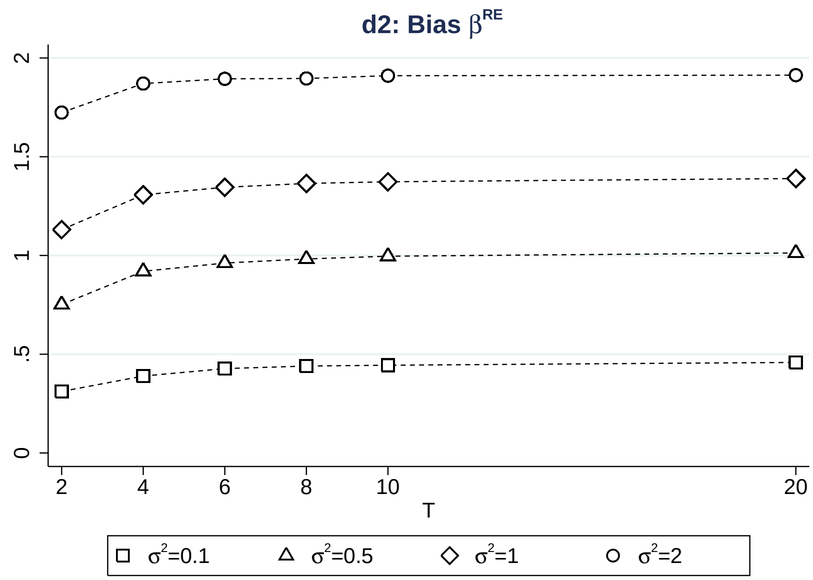

Figure A3.9: DGP 4 - $d2_i$: time-constant dummy variable. Mean value of the bias of the estimated coefficients from RE estimators (% of the true value)

Table A3.3: DGP 4 - Results from Monte Carlo experiment

		c_{it}					$d1_{it}$					$d2_i$	
		FE		RE			FE		RE			RE	
σ_a^2	T	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_c^{FE} - \hat{\beta}_c^{RE}\rvert$	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_{d1}^{FE} - \hat{\beta}_{d1}^{RE}\rvert$	bias (%)	SD
0.1	2	0.001	0.033	0.627	0.047	0.313	0.001	0.014	0.152	0.020	0.075	0.312	0.038
	4	-0.003	0.023	0.309	0.025	0.156	-0.000	0.010	0.070	0.011	0.035	0.389	0.036
	6	0.000	0.020	0.190	0.021	0.095	-0.001	0.009	0.044	0.009	0.022	0.427	0.035
	8	-0.001	0.019	0.136	0.019	0.068	0.000	0.008	0.034	0.008	0.017	0.440	0.034
	10	0.002	0.019	0.109	0.018	0.054	0.000	0.008	0.027	0.008	0.014	0.444	0.033
	20	-0.001	0.016	0.058	0.016	0.029	0.000	0.006	0.016	0.006	0.008	0.459	0.029
0.5	2	0.001	0.014	0.399	0.021	0.199	-0.001	0.014	0.204	0.020	0.102	0.752	0.048
	4	0.000	0.010	0.135	0.011	0.068	0.000	0.010	0.074	0.011	0.037	0.920	0.049
	6	0.000	0.009	0.074	0.009	0.037	0.001	0.009	0.045	0.009	0.022	0.962	0.049
	8	0.001	0.008	0.051	0.008	0.025	0.001	0.008	0.032	0.008	0.016	0.982	0.048
	10	0.001	0.008	0.039	0.008	0.019	-0.000	0.007	0.025	0.008	0.012	0.996	0.048
	20	-0.000	0.006	0.018	0.006	0.009	0.000	0.006	0.013	0.006	0.006	1.013	0.048
1	2	-0.003	0.015	0.223	0.020	0.113	0.001	0.014	0.181	0.020	0.090	1.131	0.064
	4	-0.004	0.010	0.059	0.011	0.032	0.000	0.010	0.059	0.011	0.029	1.307	0.064
	6	-0.003	0.009	0.031	0.010	0.017	0.002	0.009	0.036	0.009	0.017	1.345	0.064
	8	-0.005	0.010	0.018	0.010	0.011	0.001	0.008	0.026	0.008	0.012	1.365	0.064
	10	-0.005	0.010	0.012	0.010	0.008	0.002	0.008	0.021	0.008	0.010	1.373	0.065
	20	-0.004	0.008	0.003	0.008	0.004	0.001	0.007	0.011	0.007	0.005	1.390	0.064
2	2	-0.089	0.046	0.003	0.048	0.046	0.018	0.018	0.146	0.021	0.064	1.724	0.108
	4	-0.092	0.036	-0.070	0.037	0.011	0.027	0.015	0.067	0.015	0.020	1.871	0.099
	6	-0.094	0.033	-0.082	0.034	0.006	0.033	0.015	0.056	0.015	0.012	1.895	0.097
	8	-0.089	0.031	-0.082	0.032	0.004	0.034	0.015	0.050	0.015	0.008	1.896	0.095
	10	-0.094	0.031	-0.089	0.031	0.003	0.038	0.015	0.050	0.015	0.006	1.910	0.094
	20	-0.094	0.027	-0.092	0.027	0.001	0.045	0.014	0.051	0.014	0.003	1.913	0.093

Note: bias is calculated as percentage of the true value: $\frac{1}{R}\sum_{r=1}^{R}\left[\left(\hat{\beta}_r/\beta_0\right)-1\right]$; Number of replications $R = 1000$; Sample size for each replication $N = 1000$

DGP 5

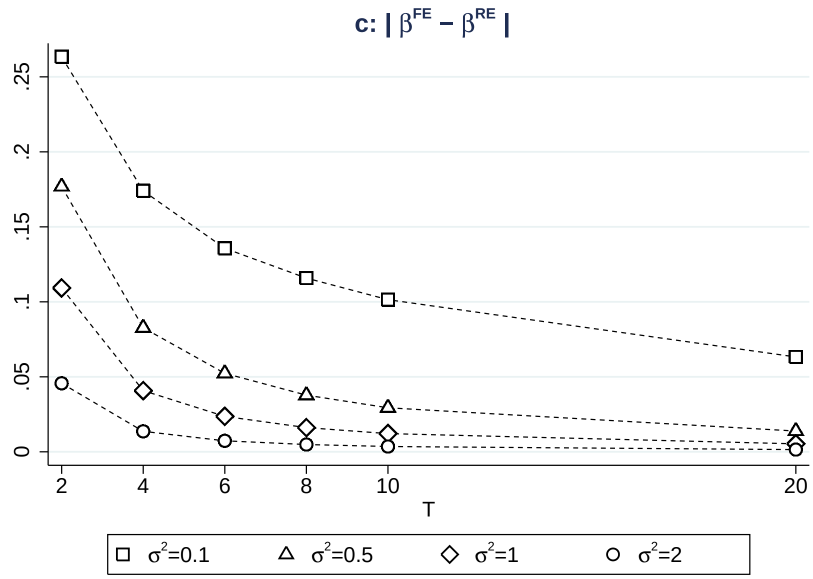

Figure A3.10: DGP 5 - c_{it}: time-varying continuous variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

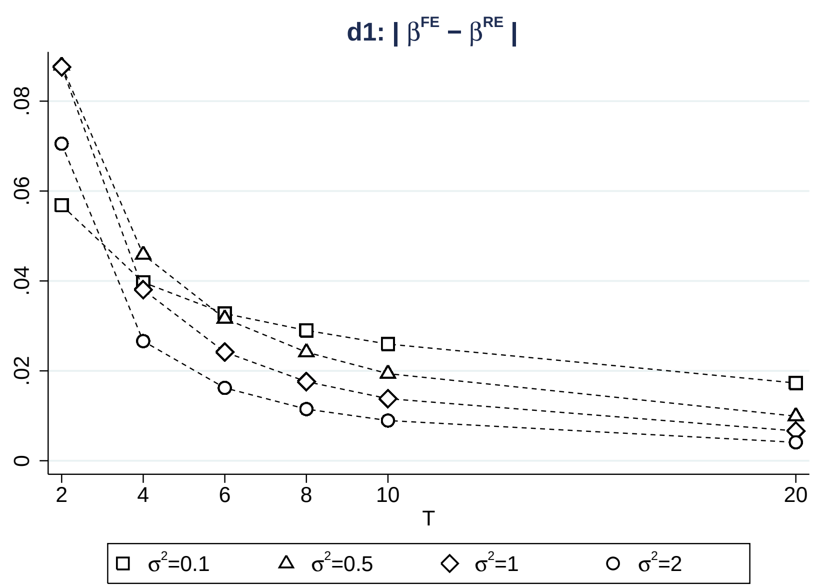

Figure A3.11: DGP 5 - $d1_{it}$: time-varying dummy variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

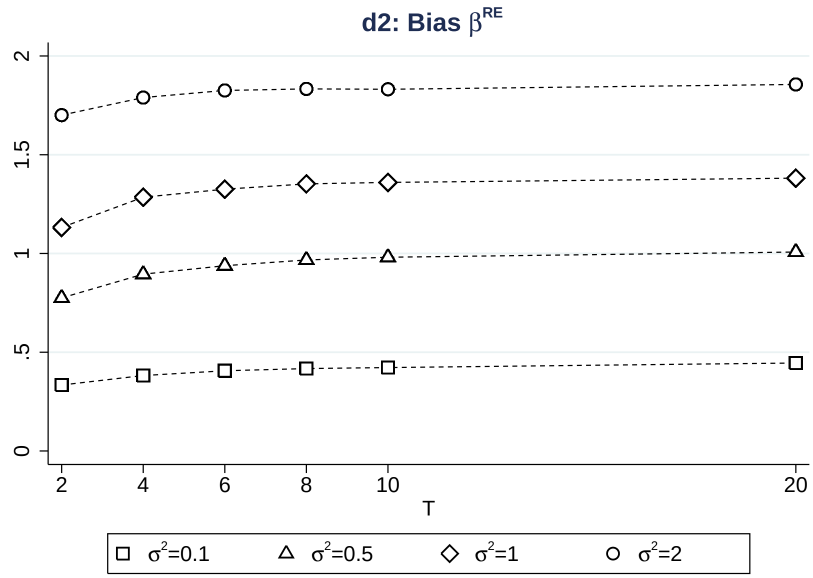

Figure A3.12: DGP 5 - $d2_i$: time-constant dummy variable. Mean value of the bias of the estimated coefficients from RE estimators (% of the true value)

Table A3.4: DGP 5 - Results from Monte Carlo experiment

		c_{it}					$d1_{it}$					$d2_i$	
		FE		RE			FE		RE			RE	
σ_a^2	T	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_c^{FE} - \hat{\beta}_c^{RE}\rvert$	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_{d1}^{FE} - \hat{\beta}_{d1}^{RE}\rvert$	bias (%)	SD
0.1	2	-0.006	0.222	0.520	0.126	0.263	0.004	0.080	0.117	0.064	0.057	0.334	0.056
	4	0.004	0.113	0.352	0.090	0.174	-0.002	0.046	0.078	0.043	0.040	0.382	0.041
	6	0.005	0.082	0.276	0.072	0.136	0.004	0.035	0.069	0.033	0.033	0.406	0.034
	8	-0.004	0.068	0.228	0.062	0.116	0.002	0.030	0.060	0.030	0.029	0.417	0.030
	10	-0.000	0.057	0.203	0.053	0.101	-0.001	0.025	0.051	0.025	0.026	0.422	0.029
	20	0.002	0.038	0.128	0.037	0.063	0.002	0.017	0.036	0.017	0.017	0.445	0.024
0.5	2	0.001	0.141	0.354	0.100	0.177	0.000	0.101	0.176	0.087	0.088	0.775	0.078
	4	0.001	0.072	0.167	0.066	0.083	0.001	0.055	0.092	0.054	0.046	0.895	0.059
	6	-0.004	0.053	0.101	0.051	0.052	0.002	0.042	0.065	0.041	0.032	0.938	0.055
	8	0.001	0.045	0.076	0.045	0.038	-0.000	0.037	0.048	0.036	0.024	0.967	0.052
	10	-0.004	0.039	0.055	0.038	0.029	0.000	0.031	0.039	0.031	0.019	0.981	0.047
	20	-0.000	0.027	0.027	0.027	0.014	0.000	0.022	0.020	0.022	0.010	1.007	0.045
1	2	0.013	0.150	0.231	0.122	0.109	0.017	0.121	0.192	0.111	0.088	1.132	0.118
	4	-0.002	0.083	0.079	0.079	0.041	0.005	0.070	0.081	0.069	0.038	1.285	0.092
	6	-0.005	0.058	0.042	0.057	0.024	0.004	0.054	0.053	0.053	0.024	1.326	0.073
	8	-0.004	0.047	0.028	0.047	0.016	-0.001	0.045	0.034	0.045	0.018	1.352	0.073
	10	-0.001	0.045	0.023	0.045	0.012	0.004	0.040	0.031	0.040	0.014	1.360	0.068
	20	-0.000	0.028	0.011	0.028	0.005	0.001	0.027	0.015	0.027	0.007	1.381	0.064
2	2	0.023	0.244	0.112	0.227	0.044	-0.003	0.177	0.137	0.168	0.070	1.701	0.437
	4	0.001	0.122	0.028	0.120	0.014	0.008	0.101	0.062	0.100	0.027	1.789	0.197
	6	-0.008	0.087	0.006	0.087	0.007	-0.002	0.077	0.030	0.076	0.016	1.825	0.132
	8	-0.005	0.078	0.005	0.078	0.005	0.003	0.068	0.026	0.068	0.011	1.833	0.125
	10	0.003	0.068	0.010	0.068	0.004	0.001	0.059	0.019	0.059	0.009	1.832	0.115
	20	-0.005	0.047	-0.002	0.047	0.001	0.003	0.042	0.011	0.042	0.004	1.856	0.099

Note: bias is calculated as percentage of the true value: $\frac{1}{R}\sum_{r=1}^{R}\left[\left(\hat{\beta}_r/\beta_0\right)-1\right]$; Number of replications $R = 1000$; Sample size for each replication $N = 1000$

DGP 6

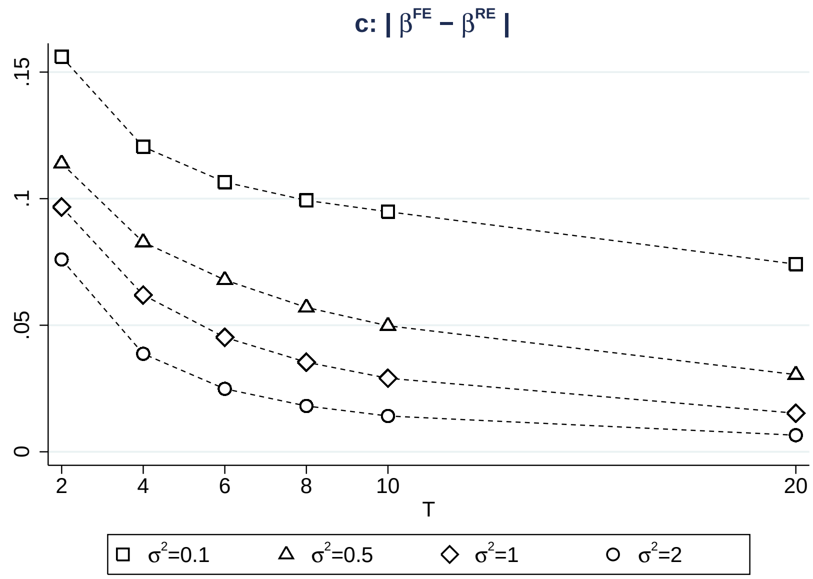

Figure A3.13: DGP 6 - c_{it}: time-varying continuous variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

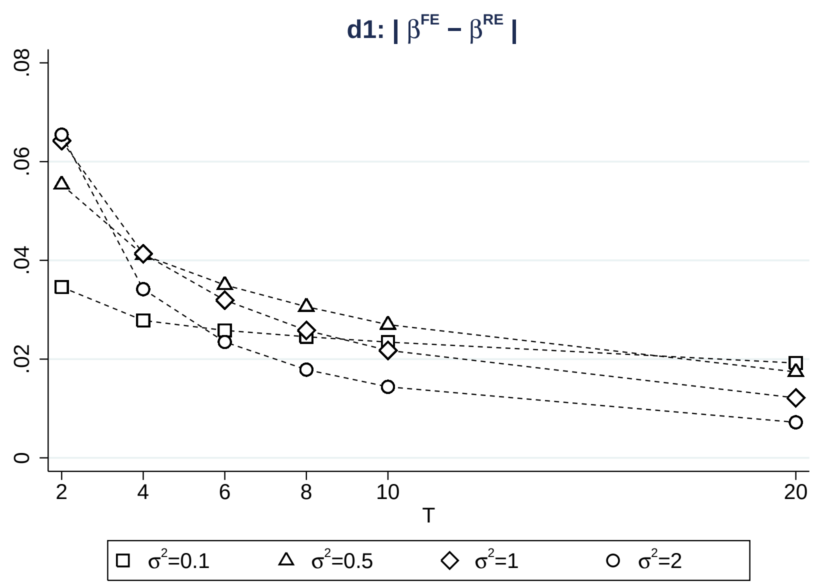

Figure A3.14: DGP 6 - $d1_{it}$: time-varying dummy variable. Mean value of the absolute difference between the estimated coefficients from FE and RE estimators

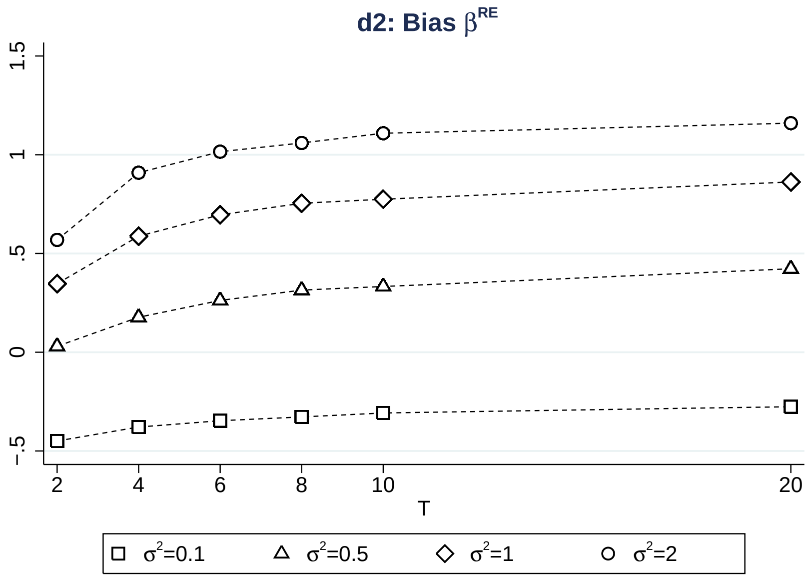

Figure A3.15: DGP 6 - $d2_i$: time-constant dummy variable. Mean value of the bias of the estimated coefficients from RE estimators (% of the true value)

Table 3.5: DGP 6 - Results from Monte Carlo experiment

		c_{it}					$d1_{it}$					$d2_i$	
		FE		RE			FE		RE			RE	
σ_a^2	T	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_c^{FE} - \hat{\beta}_c^{RE}\rvert$	bias (%)	SD	bias (%)	SD	$\lvert\hat{\beta}_{d1}^{FE} - \hat{\beta}_{d1}^{RE}\rvert$	bias (%)	SD
0.1	2	-1.084	0.149	0.082	0.081	0.151	-0.986	0.060	-0.751	0.046	0.032	-0.449	0.041
	4	-1.018	0.076	-0.090	0.055	0.120	-1.000	0.035	-0.796	0.032	0.028	-0.379	0.030
	6	-0.978	0.054	-0.158	0.043	0.107	-1.004	0.027	-0.814	0.025	0.026	-0.347	0.024
	8	-1.006	0.046	-0.241	0.038	0.099	-0.993	0.022	-0.812	0.021	0.025	-0.328	0.021
	10	-1.028	0.039	-0.298	0.034	0.095	-1.007	0.020	-0.835	0.019	0.023	-0.308	0.020
	20	-1.005	0.026	-0.434	0.025	0.074	-0.996	0.014	-0.855	0.014	0.019	-0.276	0.015
0.5	2	-1.015	0.068	-0.187	0.038	0.114	-0.998	0.059	-0.612	0.047	0.055	0.030	0.043
	4	-0.998	0.034	-0.394	0.026	0.083	-0.992	0.035	-0.705	0.032	0.041	0.177	0.036
	6	-0.999	0.025	-0.505	0.021	0.068	-1.004	0.026	-0.760	0.024	0.035	0.262	0.030
	8	-0.995	0.020	-0.579	0.019	0.057	-1.005	0.023	-0.792	0.022	0.031	0.315	0.027
	10	-0.993	0.018	-0.630	0.017	0.050	-0.999	0.020	-0.811	0.020	0.027	0.333	0.023
	20	-0.997	0.011	-0.775	0.011	0.030	-1.005	0.013	-0.885	0.013	0.017	0.423	0.021
1	2	-1.005	0.050	-0.353	0.029	0.097	-0.989	0.062	-0.575	0.052	0.064	0.347	0.051
	4	-1.000	0.026	-0.582	0.021	0.062	-1.001	0.037	-0.736	0.034	0.041	0.588	0.039
	6	-1.009	0.018	-0.704	0.016	0.045	-0.997	0.028	-0.793	0.027	0.032	0.696	0.035
	8	-0.998	0.015	-0.759	0.014	0.035	-0.996	0.024	-0.832	0.023	0.026	0.754	0.033
	10	-0.999	0.013	-0.803	0.012	0.029	-0.995	0.021	-0.857	0.021	0.022	0.775	0.030
	20	-1.002	0.008	-0.900	0.008	0.015	-0.998	0.015	-0.921	0.015	0.012	0.862	0.029
2	2	-0.995	0.037	-0.562	0.024	0.076	-0.997	0.067	-0.651	0.058	0.065	0.569	0.060
	4	-0.996	0.019	-0.776	0.017	0.039	-1.004	0.038	-0.825	0.037	0.034	0.909	0.050
	6	-1.001	0.014	-0.859	0.013	0.025	-0.999	0.032	-0.877	0.031	0.023	1.015	0.045
	8	-1.002	0.011	-0.898	0.011	0.018	-0.992	0.025	-0.899	0.025	0.018	1.060	0.044
	10	-1.004	0.009	-0.924	0.009	0.014	-1.006	0.022	-0.931	0.022	0.014	1.109	0.042
	20	-1.002	0.007	-0.965	0.007	0.007	-0.995	0.015	-0.958	0.015	0.007	1.160	0.039

Note: bias is calculated as percentage of the true value: $\frac{1}{R}\sum_{r=1}^{R}\left[\left(\left(\exp(\hat{\beta}_r)-1\right)/g(\mathrm{x}_{it},\beta_0,a_i)\right)-1\right]$; The true value $g(\mathrm{x}_{\mathrm{it}},\beta_o,a_i)$ is the true average semi-elasticity for c_{it}, and the true average proportionate difference for $d1_{it}$ and $d2_i$. Number of replications $R = 1000$; Sample size for each replication $N = 1000$