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PÉTER ELEK – JÁNOS KÖLLŐ

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Authors:

Péter Elek
assistant professor
Department of Economics
Eötvös Loránd University (ELTE), Budapest, Hungary
email: peter.elek@tatk.elte.hu

János Köllő
research advisor
Institute of Economics
Centre for Economic and Regional Studies, Hungarian Academy of Sciences
email: kollo.janos@krtk.mta.hu

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Abstract

We study the undeclared work patterns of Hungarian employees in relatively stable jobs, using a panel dataset that matches individual-level self-reported Labour Force Survey (LFS) data with administrative data from the Pension Directorate for 2001–2006. We estimate the determinants of undeclared work using Heckman-type random-effects panel probit models, and develop a two-regime model to separate permanent and transitory undeclared work, where the latter follows a Markov chain. We find that about 6 per cent of workers went permanently unreported for six consecutive years, and a further 3-4 per cent were transitorily unreported in any given year. By simulating the permanent and transitory components of undeclared work, we examine the implications for health and pension eligibility.

JEL: C23, C25, H26, J46

Keywords:
undeclared work, labour input method, matched administrative-survey data, random-effects panel probit model with endogenous selection, Markov chain

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A tartós és átmeneti feketefoglalkoztatás elkülönítése kapcsolt adminisztratív és kérdőíves adatok alapján

Elek Péter – Köllő János

Összefoglaló

A tanulmányban a viszonylag stabil állással rendelkező munkavállalók körében vizsgáljuk a feketemunkát Magyarországon egy olyan paneladatbázis segítségével, amely egyéni szinten kapcsolja össze a KSH Munkaerő-felmérésének (MEF) adatait az Országos Nyugdíjbiztosítási Főigazgatóságtól (ONYF) származó adminisztratív adatokkal a 2001-2006 közötti időszakra. A feketefoglalkoztatást befolyásoló tényezőket Heckman-féle véletlen hatású (random-effects) panel probit modellekkel becsüljük, valamint kifejlesztünk egy látens rezsimeket tartalmazó modellt is a tartós és az átmeneti feketemunka szétválasztására, ahol az utóbbit Markov-folyamattal modellezzük. Azt találjuk, hogy a munkavállalók mintegy 6 százaléka volt tartósan feketén foglalkoztatott a hat egymást követő évben, és évente 3-4 százalékukat foglalkoztatták átmenetileg feketén. Végezetül a feketemunka tartós és átmeneti komponenseinek szimulációjával az egészségügyi és nyugdíjjogosultságra kifejtett hatásokat elemezzük.

JEL: C23, C25, H26, J46

Tárgyszavak:

feketefoglalkoztatás, munkainput-módszer, kapcsolt adminisztratív és kérdőíves adatok, véletlen hatású panel probit modell endogén szelekcióval, Markov-lánc

1. INTRODUCTION

Undeclared employment – when the worker is not reported to the authorities and neither the employer nor the employee pay taxes or contributions in the relationship – is notoriously difficult to measure. Survey-based methods rely on information directly provided by the population, but these tend to underestimate the true magnitude of black work, and are strongly affected by cultural differences. For instance, according to the Eurobarometer Survey, only 4 per cent of the EU population responded in 2013 that they had undertaken undeclared paid work in the preceding year (European Commission, 2014); the highest rates were recorded in Latvia, the Netherlands, Estonia and Denmark (9–11 per cent), while Southern European countries reported very low rates (1–3 per cent in Malta, Portugal, Cyprus, Italy and Greece).

Indirect methods estimate total employment with observable proxies, and compare these with reported employment figures to obtain a measure of undeclared work. A wide range of techniques fall into this category,[1] the most promising being the *discrepancy* or *labour input* method, which was advocated by a task force as a methodologically appropriate tool for EU-wide measurement of undeclared work (GHK/FGB, 2009). This technique assumes that labour force surveys register most of the undeclared work because individuals are not motivated to conceal their true employment status in an unofficial interview. Hence undeclared work can be approximated by comparing Labour Force Survey (LFS) employment with registered employment figures, which may come from administrative sources or enterprise surveys. This method – in line with other indirect techniques (Schneider, 2012) – yields considerably larger estimates of undeclared work than do survey-based methods: e.g. 16–17 per cent of total employment in Hungary between 2001 and 2005 (Elek et al., 2009; Benedek et al., 2013) and 8–30 per cent of various macroeconomic aggregates in European countries.[2] These estimates do not suffer from the underreporting bias of surveys, but they are generally not suitable for multivariate analysis, because only group-wise comparisons are possible, across dimensions that are available in both data

[1] Examples are the consumption-income discrepancy method, the monetary method, the electricity consumption method and econometric methods such as MIMIC (Renooy et al., 2004; Schneider, 2012).

[2] For instance, 11.5 per cent of employment in full-time equivalent units for Italy in 2004 (Baldassarini, 2007), 17–21 per cent of official GDP for Slovenia between 1995 and 2004 (Nastav and Bojnec, 2007), 8 per cent of total employment for Spain in 2002 and 20–30 per cent of GDP for Romania between 1996 and 2002 (for these and other EU country results, see GHK/FGB, 2009, pp. 49 and 77).

sources. Hence, most analysis using the labour input method provides only sectoral, regional or gender-specific breakdown (GHK/FGB, 2009).

In this paper, we exploit a unique panel dataset from Hungary that matches self-reported and administrative employment data at the individual level. The data relate to workers who reported at least two years of uninterrupted tenure in the jobs they held in January–March 2008, when they were interviewed for the LFS. We assess the pensionable years they accrued in 2001–2006, using quality-checked administrative data provided by the National Pension Insurance Directorate (NPID). The matched data enable us to combine the strengths of the 'labour input' method and survey-based methods by analysing the determinants of undeclared work in a multivariate setting. We examine the data with regard to biases stemming from non-random sampling, recall bias on the part of LFS respondents, and technical failures and negligence on the part of employers, the NPID or the postal service.

Our dataset was created by asking LFS respondents to permit the NPID and the Hungarian Central Statistical Office to link their responses to their retrospective employment data stored at the NPID. The positive response rate was around 25 per cent, and the incentive offered – for an individual to acquire her official employment history – was likely to be related to the time spent undeclared; hence the matched sample is non-random. Therefore, besides using random-effects (RE) panel linear and probit models, we also estimate an RE panel probit with endogenous selection to control for self-selection. We exploit the rotating panel structure of the LFS to find suitable instruments that influence the sampling probability, without affecting the incidence of undeclared work. The model is estimated by maximum simulated likelihood, using adaptive quadrature (Rabe-Hesketh et al., 2004).

As a further advantage, the dataset allows us to separate permanent and transitory non-reporting. Of those workers who were observed in the sample for six years, around 6–7 per cent were never reported; around 3 per cent were unreported only once; and around 3.5 per cent were unreported between two and five times. We build a two-regime model, where both permanent and transitory non-reporting probabilities depend on the observables through probit link functions, and where transitory non-reporting follows a Markov chain. The model is estimated with maximum likelihood.

Retrospective data on the observed workers suggest that of the 9.5–11 per cent non-reporting ratio, more than 8 per cent was predictably due to the non-reporting of actual work activity rather than breaks in the employment relationship. The econometric estimates (especially those relating to permanently unreported workers) offer support for the hypothesis that the bulk of non-reporting reflects informal employment, because – in line with other studies – they predict lower reporting rates in, for example, agriculture and transport, various forms of atypical work, among males and in small firms. Finally, the two-regime model allows us to examine the consequences of undeclared work on access to health care and pensions.

Our analysis relates to two strands of existing literature. According to the traditional economic approach (Slemrod and Yitzhaki, 2002), economic actors make decisions about tax evasion by comparing expected fines and the amount of tax that can be evaded. Therefore, tax evasion is reduced by higher individual risk aversion, stronger deterrence and lower tax rates (Buehn and Schneider, 2012). However, it is difficult to explain willingness to pay taxes using the standard economic model – considering the limited risk of being caught and the rates of potential fines – and therefore more recent literature incorporates the effect of the social environment, such as rule following, the need to belong to groups and other interactions (Feld and Larsen, 2012; Pickhardt and Prinz, 2014). The monopsonistic position of employers and the low bargaining power of employees may also be important (Cichocki and Tyrowicz, 2010). Our estimates of differences in undeclared work across gender, level of education, work experience, occupation, place of residence, sector, size and ownership of the employer provide insight into how differences in risk aversion, the expected costs of cheating and social interactions influence the prevalence of undeclared work. These results complement already existing cross-sectional multivariate analyses of undeclared work, which are, however, mainly available from survey-based studies (Williams, 2007; Feld and Larsen, 2012; European Commission, 2014).

By giving a detailed description of the dynamics of non-reporting, our approach is also related to the literature that models measurement error in earnings using matched administrative and survey data (Pischke, 1995; Abowd and Stinson, 2013). A few papers focus specifically on tax evasion using matched microdata (Baldini et al., 2009; Paulus, 2015). However, in contrast to our paper, that stream of literature does not concentrate on undeclared work (i.e. full income tax evasion) and also follows a different econometrics modelling framework, because earnings are continuous, whereas our undeclared work dummy is a binary variable.

The paper is organized as follows. Section 2 introduces the dataset, Section 3 describes the econometric models, while Section 4 provides the multivariate results and sheds light on long-term consequences with simulations. Finally, Section 5 offers some conclusions.

2. DATA AND DESCRIPTIVE STATISTICS

2.1 DATA

Formation of the sample. As was already mentioned, in January–March 2008, LFS respondents were offered the chance to obtain precise information about their registered accrual years, and were asked in return to permit the NPID and the Hungarian Central Statistical Office to use their merged data for research purposes.[3] The dataset created in this way contains all variables of the LFS wave and the respondents' annual reported days in work between their first appearance in the NPID register and December 2007.

We omit the data for 2007 because there is a delay in compiling and quality-checking the NPID register, which makes the 2007 data unreliable. By excluding workers who started their spells in work in January 2006 or later, we underestimate the incidence of black work, since this is expected to occur more frequently in marginal, high-turnover jobs.

We also restrict the period of observation from below. As shown in Figure A1 in the Appendix, the reporting rate of small firms was low before 1999 (see Köllő, 2015 for more details). In 1999, when firms were obliged for the first time to add their tax ID to their pension contribution reports, the propensity of small firms to report leapt and then fell slightly in 2000. As from 2001, reporting rates settled down at levels that have continued until recently. Therefore, we restrict our analysis to 2001–2006. After this restriction, we end up with a sample of 23,385 person-years, covering 4,707 workers.

Dealing with biases. Our key variable measures reported days in each full year that the respondent spent with the employer: if the worker entered the firm in year t, we measure her reported days in years $t+1$, $t+2$, ..., 2006. Registered days within a full year can vary between zero and 365 (or 366), since holidays and paid leave are counted as insured periods. We would expect 100 per cent of the time that workers spent with their employers to appear in the NPID register, and so we can interpret the difference between reported and total days as a measure of unregistered work. However, our key measure is subject to biases for at least three reasons: (i) the sample is non-random; (ii) employment spells perceived by the LFS respondents as continuous may not be

[3] Hungarians typically have no precise information on their accumulated accrual points and expected pensions before they actually retire. The computer records (since 1988) and printed material that records registered workdays and contribution payments are available to individuals before their retirement only after a lengthy administrative procedure.

regarded as continuous by the NPID; and (iii) some NPID records may be missing for technical reasons (unsent or lost).

Sample selection bias. Of the 31,195 LFS respondents over 15 years of age and not in receipt of a pension in 2008, some 7,654 (25 per cent) requested information from the NPID (of these, 4,707 were employed according to the LFS). Selection for the LFS–NPID sample was presumably non-random. We allow for self-selection in two ways. First, we use observables to estimate the probability (p) that an LFS respondent requested information from the NPID (see the selection equation later in Section 3.2 and the results in Table 5) and apply $1/p$ and the product of $1/p$ and the LFS weight (w/p) as weights, to give a reweighted estimate of aggregate non-reporting. Statistics with and without weighting suggest that the results are weakly affected by the weighting scheme (see Table 1). For further details, see Bálint et al. (2010).

Beyond observables, selection to the LFS–NPID sample could potentially be affected by unobservables that also influence the probability of undeclared work. To tackle this problem, we use two instrumental variables that are correlated with the probability of being in the sample, but are uncorrelated with registration history. We discuss these in detail in Section 3.2.

Unreported work versus temporary breaks. The share of declared working days during a permanent-looking employment spell may fall short of the expected 100 per cent for reasons other than non-reporting. Seasonal slumps, stoppages, strikes, unpaid leave and absenteeism may cause breaks in the spell of employment, without dissolution of the employment relationship. Thanks to retrospective questions in the LFS, we are in a position to measure the incidence of such 'real' breaks with some precision. The event of interest is non-employment (by ILO/OECD standards) during a permanent employment relationship. For the study of such events, we selected employed workers from the 2001–2006 waves of the LFS, who had entered their jobs more than 12 months before the LFS interview and counted those who said that exactly 12 months before the interview they had not been working. However, only a tiny minority – around 1.5 per cent – of those in permanent employment reported breaks in work. These figures, compared to 9.5–11 per cent missing from the NPID register (Table 1), suggest that the difference between LFS-reported and registered employment stems primarily from underreporting.

Accounting for administrative failure. Unsent and lost reports are unlikely to explain why one's NPID data are missing for protracted periods, but they can inflate our non-reporting measure for shorter terms. Therefore, we shall pay due attention to the duration of non-reporting by estimating a joint model for short (especially one year long) and permanent spells of unreported work.

2.2 DESCRIPTIVE STATISTICS

As shown in Table 1, depending on the weighting method, some 9.5–11 per cent of working days were unreported to the NPID on average in 2001–2006. Underreporting means no reporting at all in the vast majority of cases: in the unweighted sample, instances where the firm did not report the employment relationship at all in a given year accounted for 8 of the missing 9.5 per cent. In the forthcoming sections we will regard a worker as 'unreported' if the fraction of her reported days falls short of 50 per cent of all days in a given year – the average of this dummy variable (9.2 per cent) is roughly the same as the ratio of unreported days (9.5 per cent in the unweighted sample).

Table 1

Non-reporting rates (2001–2006 annual averages, per cent)

	Unreported days	Zero per cent	Less than 50 per cent	Less than 95 per cent
		of workdays reported in the given year		
Unweighted sample	9.5	8.0	9.2	11.7
Weighted with LFS weights (w)	9.9	8.4	9.6	12.1
Weighted with 1/p	10.2	8.4	9.9	12.7
Weighted with w/p	11.0	9.2	10.6	13.5

Note: matched LFS–NPID sample. p = estimated sampling probability based on observables. Number of observations: 23,385 person-years covering 4,707 workers.

These estimates of undeclared work are substantial, but – as a result of focusing on relatively stable jobs – are smaller than the figures obtained by comparing aggregate LFS and NPID employment data, which yield 16–17 per cent for undeclared work in Hungary in 2001–2006 (Elek et al., 2009 and Benedek et al., 2013 for 2001–2005; own calculations for 2006).

Table 2 draws attention to three sizeable unreported groups. Among workers observed throughout the period of six years, around 50 per cent were permanently unreported, 25 per cent had a single unreported year, and a further 25 per cent were unreported 2–5 times (6.5, 3.2 and 3.5 per cent, respectively). Single-year and permanent non-reporting dominate in groups observed for shorter periods as well.

Table 2

The distribution of observed workers by number of years in the sample and number of unreported years

Number of workers	Unreported years								
Years in sample	0	1	2	3	4	5	6	Total	Per cent
1	325	29	0	0	0	0	0	354	7.5%
2	283	24	22	0	0	0	0	329	7.0%
3	264	17	3	11	0	0	0	295	6.3%
4	248	24	9	3	27	0	0	311	6.6%
5	212	19	10	4	4	15	0	264	5.6%
6	2,735	102	42	24	19	26	206	3,154	67.0%
Total	4,067	215	86	42	50	41	206	4,707	100.0%
Per cent									
if years in sample = 6	86.7	3.2	1.3	0.8	0.6	0.8	6.5	100.0	
in Total	86.4	4.6	1.8	0.9	1.1	0.9	4.4	100.0	
in Total	all years unreported (i.e. diagonal elements) = 6.6%								

Note: matched LFS–NPID sample. Unreported year = less than half of the workdays are reported.

Transition probabilities between reported and unreported spells are displayed in Table 3 for those who were declared to the authorities at least once during their observed employment period. On average, 1.1 per cent of reported workers became unreported in the next period, and around half of the temporarily (i.e. not permanently) unreported workers returned to a reported state one year later.

Table 3

Transition probabilities between reported and unreported years among workers who were reported at least once during their observed employment period

	Last year		If last year = unreported			
	Reported	Unreported	If previous unreported spell			If tenure
This year			= 1 year	> 1 year	unknown	= 1 year
Number of workers						
Reported	16,751	259	65	84	29	81
Unreported	189	269	72	136	39	22
Per cent						
Reported	98.9	49.0	47.4	38.2	42.6	78.6
Unreported	1.1	51.0	52.6	61.8	57.4	21.4

Note: matched LFS–NPID sample. The unreported spell has unknown duration for left-censored observations. Tenure refers to the number of years in the current job.
Number of observations: 17,468 person-years covering 4,073 workers who were reported at least once during their observed employment spell.

The probabilities of returning to reported work after one year, after more than one year, or – in the case of a left-censored duration – after an unknown number of unreported years are around 40–50 per cent, and do not differ significantly from each other,[4] suggesting that the dynamics of temporary non-reporting follows a Markov chain, with an average duration of two years in the unreported state. There is one exception to this simple Markov rule: people who were unreported in their first full year in their current job had a significantly higher (around 80 per cent) probability of transition to reported work after that year (Table 3). This will be taken into account in model building.

Table A1 in the Appendix summarizes average non-reporting rates in selected groups. Men are more likely to be unreported, and are much more likely than women to be permanently unreported. Undeclared work occurs most frequently among workers with secondary education (some of them awaiting college admission) and least frequently among those with a university degree; the differences by education are larger for permanent non-reporting. The reporting rates are low for the self-employed; very low for casual workers; and below average among farmers, skilled service and construction workers, porters, guards and people doing elementary jobs. Part-timers are less likely to be reported than are full-timers. Undeclared work is very frequent in telework. Also, people in their first full year in their current job are about 3 percentage points more likely to be unreported than other workers.

Foreign-owned firms have a much lower non-reporting rate than domestically owned firms (3 versus 10 per cent). The share of unreported days does not exceed 7 per cent in firms that employ five or more workers, but is around 12 per cent in firms employing 2–4 workers and exceeds 30 per cent in sole proprietorships. Permanent undeclared work seems to be more heterogeneous across groups than transitory non-reporting.

3. METHODS

3.1 BASELINE MODELS

In our baseline specifications, we apply random-effects (RE) linear and probit models to identify the impact of demographic and economic variables on the prevalence of undeclared work:

[4] Homogeneity of the three distributions is not rejected by a chi-squared test (p-value is 0.22).

(1) $$R_{it} = \boldsymbol{X}_{it}\boldsymbol{\beta}_N + c_i^N + u_{it}^N,$$

(2) $$Q_{it} = I\{\boldsymbol{X}_{it}\boldsymbol{\beta}_P + c_i^P + u_{it}^P > 0\},$$

where the dependent variables are R_{it}, the ratio of unreported days, and Q_{it}, the dummy variable of being unreported in more than half of the year for person i in year t. The indicator function of event A is denoted by $I\{A\}$. The time-varying error term u_{it}^P follows a standard normal distribution in the probit case, while the distribution of u_{it}^N may be left unspecified (apart from a zero-mean restriction) in the linear case. The individual-level unobserved heterogeneities (c_i^N and c_i^P) have zero mean, are independent of the u_{it}-s and of the explanatory variables, and follow – in the probit case – a normal distribution.

Vector $\boldsymbol{X}_{it}$ denotes the constant and the individual- and firm-level explanatory variables, while $\boldsymbol{\beta}_N$, $\boldsymbol{\beta}_P$ are their parameters in the two models. Some of these variables (such as tenure, work experience and year fixed effects) are time-varying, but others – as a consequence of the survey design (see Section 2.1) – are measured in 2008 in the LFS. These include personal characteristics (gender, level of education, dummy for capital Budapest, unemployment rate of the micro-region), employer characteristics (sector, firm size, firm ownership), type of employment and other employment variables (part-time and atypical employment, telework, irregular work patterns). For the full list of variables, see Tables 4 and 5.

The majority of the above variables are either fixed in time (such as gender) or can be treated as time-invariant because they refer to the individual's work history within the same firm (e.g. sector of the firm). Nevertheless, some variables (such as firm size, firm ownership or type of employment) may have changed during the employment spell, and this should be taken into account when interpreting the parameter estimates.

We estimate the RE linear model by RE-GLS, and display autocorrelation- and heteroscedasticity-robust standard errors. We estimate the RE probit model using maximum simulated likelihood (MSL) with adaptive Gauss–Hermite quadrature.[5] To compare results with the RE linear model, we also calculate the average marginal

[5] The likelihood function in the RE probit model is given as an integral with respect to the unobserved heterogeneity c_i^P. In the MSL procedure this is approximated with adaptive Gauss–Hermite quadrature and then maximized. We use 12 integration points, but the results are not sensitive to this choice. Technically, the estimates are obtained with the xtprobit command of the Stata software (version 12).

effects of the variables on $\Pr(Q_{it} = 1)$ from the RE probit model, where we integrate out the c_i^P random effects.[6]

3.2 MODEL WITH ENDOGENOUS SELECTION

As described in detail in Section 2.1, selection into the panel dataset was non-random. The incentive for an individual to obtain her official employment history is likely to have been directly related to the time spent undeclared, the dependent variable in the equations. Hence the parameter estimates on the selected sample are not necessarily consistent. This is a Heckman-type selection problem, and one solution is to find suitable instrumental variables (IVs) that influence the sampling probability, but otherwise can be treated as random in relation to the prevalence of undeclared work. Since the LFS is a rotating panel, where units are followed for up to six consecutive quarters, one candidate for such an IV is the sequence number of the visit of the pollster, when she asked the respondent for permission to be included in the matched LFS–NPID sample. On average, the first visit of the pollster takes much longer and is more elaborate than subsequent visits, because it takes time to get acquainted with the sampled household, give the members an overview of the LFS and inform them of the possibility to obtain information about their accrual years. Hence we expect – and in fact we find (see Table 4 in Section 4.1) – that the first LFS visit is associated with a greater probability of getting into the matched sample than are subsequent visits, even after controlling for the observables. On the other hand, the quarter in which a respondent first appears in the LFS is random, and hence the sequence number of the LFS visit is unrelated to the respondent's time spent undeclared.

A second possible IV is the duration of the LFS interview, which is also recorded in the LFS database. A longer interview is associated with a higher sampling probability, even after controlling for the observables (Table 4). However, we do not expect it to be related to the prevalence of undeclared work.

We model selection into the matched LFS–NPID panel in a probit framework:

$$S_i = I\{\boldsymbol{X}_i\boldsymbol{\delta} + \boldsymbol{Z}_i\boldsymbol{\eta} + v_i > 0\}, \tag{3}$$

where S_i denotes the dummy variable for being included in the matched LFS–NPID sample, $\boldsymbol{Z}_i$ is the vector of the above two IVs, $\boldsymbol{X}_i$ is the vector of observables in year 2006 (i.e. $\boldsymbol{X}_i = \boldsymbol{X}_{i,2006}$), which are all calculated from the LFS and hence are observed

[6] The average marginal effects are calculated using the gllapred command of the GLLAMM package of Stata, after bootstrapping the estimated model 1,000 times.

for all respondents, not just for those in the matched sample, $\boldsymbol{\delta}$ and $\boldsymbol{\eta}$ are the corresponding parameter vectors, and v_i is a standard normally distributed random variable.

The structural equation for the dummy variable of undeclared work is given by the panel probit model (equation (2)),[7] but data for that equation are only available on the matched sample ($S_i = 1$). In the model of endogenous selection, the two equations ((2) and (3)) are related by the assumption that

(4) $\quad \mathrm{corr}(v_i, c_i^P) = \rho.$

If $\rho = 0$, then equation (3) does not provide additional information on the structural equation (2), but otherwise the two equations should be tackled jointly. We estimate the system with maximum simulated likelihood, using adaptive quadrature.[8] We calculate the average marginal effects of the explanatory variables on $\Pr(Q_{it} = 1)$, with the c_i^P random effects integrated out.

The reciprocal of the sampling probabilities estimated from equation (3) was used as a weight to obtain the aggregate prevalence of non-reporting in Table 1.

3.3 SEPARATING PERMANENT AND TRANSITORY NON-REPORTING

The above panel regressions do not explicitly model the time series properties of the non-reporting process, although such a dynamic model – if well specified – could not only be used in long-term dynamic simulations, but would also give more efficient estimates of the effects of observables on undeclared work. The descriptive results in Tables 2 and 3 suggest that Q_{it}, the dummy for undeclared work,[9] follows a two-regime model: either $Q_{it} = 1$ holds for all years (permanent undeclared work) for a particular person, or Q_{it} is – conditionally on the observables – a Markov chain (transitory undeclared work).

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[7] We do not use the linear specification (equation (1)) in models with endogenous selection, because the estimation of such models depends crucially on distributional assumptions imposed on the error terms (e.g. normality). R_{it} is close to binary, and hence a binary model on Q_{it} is more appropriate.
[8] Technically, the system is estimated using the GLLAMM package of the Stata software (Rabe-Hesketh et al., 2004).
[9] To keep the model structure relatively simple, we do not incorporate endogenous selection into the two-regime model. According to Section 4.2, the model with endogenous selection yields qualitatively similar results to the baseline ones.

More formally, let person i have explanatory variables $\boldsymbol{X}_{it}$ in year t (and in particular the tenure in her current job in years, C_{it}), time-independent explanatory variables $\boldsymbol{X}_i$,[10] and let us denote her latent (unobservable) regime by J_i, which can take value 1 (permanent non-reporting) or 0 (transitory non-reporting). The probability of the permanent regime is given by:

(5) $\Pr(J_i = 1 \mid \boldsymbol{X}_i) = \Phi(\boldsymbol{X}_i \boldsymbol{\beta}_Z)$,

where Φ stands for the standard normal distribution function and $\boldsymbol{\beta}_Z$ is the parameter vector describing the probability of permanent undeclared work.

The conditional probability of being undeclared is trivial for the permanent regime:

(6) $\Pr(Q_{it} = 1 \mid J_i = 1) = 1$

while it is given as a function of the previous year's state for the transitory regime:

(7) $\Pr\big(Q_{it} = 1 \mid \big(Q_{i,t-1} = 0 \text{ or } C_{it} = 1\big), J_i = 0, \boldsymbol{X}_{it}\big) = \Phi(\boldsymbol{X}_{it}\boldsymbol{\beta}_T) = p_{it}^{(01)} = 1 - p_{it}^{(00)}$

(8) $\Pr\big(Q_{it} = 1 \mid Q_{i,t-1} = 1, J_i = 0, \boldsymbol{X}_{it}\big) = 1 - \Phi(r_0 + r_1 * I\{C_{it} = 2\}) =$

$$= p_{it}^{(11)} = 1 - p_{it}^{(10)},$$

where $\boldsymbol{\beta}_T$ is the parameter vector determining the transition probability from the reported to the unreported state, while the transition probability in the other direction is given by $\Phi(r_0)$ in general and $\Phi(r_0 + r_1)$ specifically after the first full year of tenure. The probabilities in the first year of tenure (i.e. when $C_{it} = 1$ and hence $Q_{i,t-1}$ is not defined) are formally the same as for $Q_{i,t-1} = 0$, but in practice they may differ because $\boldsymbol{X}_{it}$ contains C_{it}. Finally, $p_{it}^{(01)}$, $p_{it}^{(00)}$, $p_{it}^{(11)}$ and $p_{it}^{(10)}$ are just short notations for the corresponding transition probabilities. Because of the small sample size in transitory non-reporting (see Table 3), we do not model $p_{it}^{(11)}$ as a function of observables beyond C_{it}.

Although J_i is not observed (a worker can be unreported by chance throughout her observed employment spell, even if she belongs to the transitory regime), the model can

[10] The notation here differs slightly from the previous section because $\boldsymbol{X}_i$ now does not contain the year 2006 values of the time-varying variables (work experience and tenure).

be estimated by maximum likelihood. Indeed, the likelihood function can be obtained by distinguishing between the cases of being reported at least once and never being reported. Let t_i denote worker i's first year in the sample (which can take values between 2001 and 2006) and let us use the notations $p_{it}^{(k)} = \Pr(Q_{it} = k \mid J_i = 0, \boldsymbol{X}_{it})$ for the probability of transitory non-reporting ($k = 1$) and reporting ($k = 0$), respectively, at time t. If $\prod_{t=t_i}^{2006} Q_{it} = 0$ (i.e. if the person is reported at least once), then for $k_t \in \{0,1\}$ $(t = t_i, \ldots, 2006)$:

$$(9) \qquad \Pr\left(\bigcap_{t=t_i}^{2006}\{Q_{it} = k_t\} \mid \{\boldsymbol{X}_{it}\}\right) = \left(1 - \Phi(\boldsymbol{X}_i\boldsymbol{\beta}_Z)\right) * p_{i,t_i}^{\left(k_{t_i}\right)} * \prod_{t=t_i+1}^{2006} p_{it}^{(k_{t-1},k_t)}$$

and if $\prod_{t=t_i}^{2006} Q_{it} = 1$ (i.e. if the person is never reported), then

$$(10) \ \Pr\left(\bigcap_{t=t_i}^{2006}\{Q_{it} = 1\} \mid \{\boldsymbol{X}_{it}\}\right) = \Phi(\boldsymbol{X}_i\boldsymbol{\beta}_Z) + \left(1 - \Phi(\boldsymbol{X}_i\boldsymbol{\beta}_Z)\right) * p_{i,t_i}^{(1)} * \prod_{t=t_i+1}^{2006} p_{it}^{(11)}.$$

The first term in the latter expression shows the contribution of the permanent regime; the second term that of the transitory regime.

For workers who entered the sample at the start of their current job (i.e. for whom $C_{i,t_i} = 1$), equation (7) implies that $p_{i,t_i}^{(k)} = p_{i,t_i}^{(0,k)}$ and hence the likelihood calculation is complete for them. However, the majority of our observations are left-censored because $C_{i,2001} > 1$ for most workers who entered our sample in 2001. The missing observations from their work history can be tackled, for instance, using the expectation-maximization (EM) algorithm, or we can follow a computationally less intensive but equally satisfactory approach. Indeed, we first note that $p_{it}^{(1)}$ can be calculated recursively:

$$(11) \qquad p_{it}^{(1)} = p_{it}^{(11)} * p_{i,t-1}^{(1)} + p_{it}^{(01)} * \left(1 - p_{i,t-1}^{(1)}\right),$$

hence, to obtain $p_{i,2001}^{(1)}$ and $p_{i,2001}^{(0)}$ – only they are needed in equations (9)–(10) for the likelihood – we can go back to (for example) year 1997 and approximate $p_{i,1997}^{(1)}$ as the stationary distribution of the two-state Markov chain whose transition probabilities are fixed at their 1997 levels:

$$(12) \qquad p_{i,1997}^{(1)} \approx p_{i,1997}^{(01)} \Big/ \left(p_{i,1997}^{(10)} + p_{i,1997}^{(01)}\right).$$

This final step is only an approximation, because (1) the transition probabilities are slightly time-varying and (2) the Markov chain may not have reached the stationary distribution for some workers by 1997. Nevertheless, since the probability of return to the reported state, $p_{it}^{(10)}$, turns out to be relatively large in our case (see Section 4.1), the corresponding Markov chain has good mixing properties, and it seems to be enough to go back four years in time to get a satisfactory approximation for $p_{i,2001}^{(1)}$ in equations (9)–(10). We note that the maximum likelihood estimates turn out to be almost identical, irrespective of whether 1996, 1997 or 1998 is used as the start year in the approximation.

After estimating the two-regime model with maximum likelihood, we also calculate the average marginal effects of the covariates on the permanent and transitory non-reporting probabilities, using the probit link functions.

4. RESULTS

4.1 GENERAL FINDINGS

Turning to the multivariate results, Table 4 displays the parameter estimates of the RE probit model (equation (2)), the RE probit model with endogenous selection (equations (2)–(4) estimated as a system), and the two-regime model that separates permanent and transitory undeclared work (equations (5)–(8)). Table 5 shows the average marginal effects calculated from these models and from the simple RE linear model (equation (1)).

We first make some general remarks on the estimates. As expected, the correlation between the error terms of the selection and the structural equation in the endogenous model is significantly negative ($\rho < 0$ in equation (4)), i.e. undeclared workers were less likely to allow the researchers to obtain their official employment history. However, the majority of the marginal effect estimates are similar in the RE probit models with and without endogenous selection, although the standard errors are larger and thus some estimates are insignificant in the former. Hence we summarize the results from these models together.

According to the two-regime model, the average probability of belonging to the permanent regime was around 5.6 per cent. This is somewhat smaller than the observed ratio of never-reported respondents (see Table 2), because some workers in the transitory regime happen to be unreported during their whole observed period. If a worker was in the transitory regime, her average transition probability was 1.8 per cent from the reported to the non-reported state, and 36 per cent in the other direction (64 per cent after the first full year of tenure at the current employer, and 34 per cent otherwise). Although the unreported dummy does not have a stationary distribution in the transitory regime because of the time-varying transition probabilities, we can simulate the transitions in our six-year-wide window of observation and find that the average probability of being in the non-reported state – conditionally on being in the transitory regime – was around 3.7 per cent. Taking permanent and transitory non-reporting together, the average simulated ratio of being unreported in a given year is around 9.0 per cent, in good accordance with the observed ratio. Further details of goodness of fit of the two-regime model are given in Section 4.3.

Table 4

Parameter estimates of the multivariate models

	RE probit		RE probit with selection				Permanent regime		Transitory regime	
			structural		selection				reporting to non-reporting	
	(equation (2))		(equation (2))		(equation (3))		(equation (5))		(equation (7))	
Gender										
Male	0.79***	(0.13)	1.0***	(0.15)	-0.076***	(0.026)	0.56***	(0.10)	0.12**	(0.053)
Level of education (2008) (baseline = vocational or general secondary school)										
Primary or less (0–8 classes)	-0.32*	(0.19)	0.0016	(0.22)	-0.12***	(0.040)	-0.40***	(0.15)	0.032	(0.080)
Apprentice-based vocational	-0.36***	(0.13)	-0.29*	(0.16)	-0.021	(0.030)	-0.41***	(0.11)	0.044	(0.058)
College	-0.36*	(0.19)	-0.25	(0.24)	0.030	(0.041)	-0.33**	(0.16)	0.059	(0.081)
University	-0.86***	(0.29)	-0.36	(0.44)	-0.24***	(0.054)	-0.66**	(0.27)	-0.048	(0.12)
Tenure in current job										
First full year	0.53***	(0.095)	0.65***	(0.11)	0.0022	(0.0015)			0.67***	(0.066)
Number of years x 10	-0.15**	(0.071)	-0.19**	(0.086)					-0.097***	(0.034)
Work experience since leaving school										
Number of years x 10	-1.5***	(0.22)	-2.3***	(0.28)	0.90***	(0.056)			-0.56***	(0.10)
Squared number of years x 100	0.31***	(0.049)	0.42***	(0.060)	-0.14***	(0.011)			0.12***	(0.023)
Type of employment relationship (2008) (baseline = employee)										
Employee of a sole proprietor	0.47*	(0.26)	0.73**	(0.34)	0.0049	(0.061)	-0.17	(0.29)	0.34***	(0.098)
Casual worker	9.3***	(1.5)	12.5***	(0.95)	-0.35	(0.22)	3.4***	(0.74)	1.5**	(0.77)
Self-employed	0.19	(0.26)	0.28	(0.37)	-0.14**	(0.066)	0.35	(0.22)	-0.025	(0.12)
Member of an unincorporated company	-0.59*	(0.35)	-0.56	(0.44)	-0.11	(0.074)	-0.31	(0.30)	-0.11	(0.14)
Work schedule (2008)										
Part-time	2.4***	(0.31)	3.1***	(0.34)	-0.22***	(0.067)	1.0***	(0.21)	0.60***	(0.11)
Evening, night, weekend work	0.21*	(0.12)	0.34**	(0.14)	-0.0082	(0.026)	0.19**	(0.095)	-0.031	(0.052)
Telework	1.21***	(0.32)	1.2***	(0.38)	0.072	(0.073)	0.59***	(0.17)	0.083	(0.12)
Irregular work pattern	0.52***	(0.16)	0.70***	(0.18)	-0.027	(0.039)	0.21*	(0.11)	0.13*	(0.072)
Firm ownership (2008)										
Foreign (more than 50 per cent)	-0.60***	(0.22)	-0.53**	(0.27)	0.0018	(0.039)	-0.22	(0.23)	-0.23**	(0.092)

Firm size (number of employees, 2008) (baseline = more than 10)										
1	2.02***	(0.32)	3.0***	(0.42)	-0.061	(0.076)	0.58**	(0.23)	0.47***	(0.13)
2–4	0.40**	(0.19)	0.50**	(0.25)	-0.047	(0.045)	0.092	(0.18)	0.010	(0.084)
5–10	-0.17	(0.22)	-0.23	(0.27)	0.030	(0.045)	-0.74*	(0.38)	0.091	(0.082)
does not know (but < 11)	0.51	(0.47)	0.62	(0.65)	-0.14	(0.11)	0.26	(0.38)	-0.098	(0.24)
Economic sector (2008) (baseline = industry)										
Agriculture	1.95***	(0.20)	1.6***	(0.31)	0.23***	(0.052)	0.99***	(0.16)	0.28***	(0.090)
Construction	0.70***	(0.23)	1.1***	(0.28)	-0.21***	(0.052)	0.0011	(0.30)	0.32***	(0.093)
Transportation	2.6***	(0.23)	3.7***	(0.27)	-0.048	(0.053)	1.3***	(0.16)	0.23**	(0.10)
Trade and accommodation	0.047	(0.21)	0.39	(0.25)	-0.18***	(0.040)	-0.37	(0.26)	0.059	(0.081)
Services	0.39*	(0.21)	0.60**	(0.27)	-0.14***	(0.044)	0.047	(0.22)	0.20**	(0.085)
Education, health, public admin.	0.77***	(0.18)	0.79***	(0.21)	-0.039	(0.038)	0.61***	(0.16)	0.053	(0.078)
Region (2008)										
Micro-regional unemployment rate	2.5**	(1.1)	-0.39	(1.3)	0.016***	(0.0025)	2.1**	(0.85)	-0.46	(0.50)
Capital Budapest	1.1***	(0.26)	2.3***	(0.36)	-0.62***	(0.052)	0.56**	(0.22)	0.21*	(0.11)
Year (baseline = 2001)										
Year: 2002	0.042	(0.097)	0.087	(0.11)					-0.015	(0.076)
Year: 2003	-0.021	(0.097)	0.036	(0.11)					0.0022	(0.074)
Year: 2004	-0.099	(0.099)	-0.027	(0.11)					-0.11	(0.076)
Year: 2005	-0.22**	(0.10)	-0.16	(0.11)					-0.13*	(0.077)
Year: 2006	-0.13	(0.10)	-0.020	(0.12)					-0.041	(0.071)
Exogenous variables in selection equation (2008)										
Sequence number of LFS visit					-0.029***	(0.0069)				
Length of LFS interview (minute)					0.022***	(0.0025)				
Constant	-4.4***	(0.32)	-2.8***	(0.43)	-2.1***	(0.087)	-2.7***	(0.19)	-1.8***	(0.14)
									non-reporting to reporting (equation (8))	
First full year in current job									0.77***	(0.13)
Constant									-0.40***	(0.075)
$\sigma(c_i)$	3.2***	(0.066)	6.9***	(0.40)						
ρ (in equation (4))			-0.50***	(0.044)						

Note: matched LFS–NPID sample. The RE probit models with and without selection were estimated with maximum simulated likelihood using adaptive quadrature with 12 integration points. The two-regime model was estimated with maximum likelihood.
See Table 5 for the parameter estimates of the RE linear model (equation (1)). Additional parameter estimates of that model: $\sigma(c_i) = 0.23$ and $\sigma(u_{it}) = 0.12$.
All explanatory variables except for work experience and tenure refer to year 2008 measurements in LFS.
Number of person-years: 23,385. Number of people: 4,707. Notations for significance: *: p<0.1; **: p<0.05; ***: p<0.01.

Table 5

Average marginal effects on the percentage probability of undeclared work from the multivariate models

	RE linear (equation (1))		RE probit (equation (2))		RE probit with selection (equation (2))		Permanent regime (equation (5))		Transitory regime from reporting to non-reporting (equation (7))	
(Average estimated probability)							*5.6*	*(0.36)*	*1.8*	*(0.11)*
Gender										
Male	3.8***	(0.86)	3.3***	(0.55)	4.2***	(0.9)	4.2***	(0.81)	0.46**	(0.21)
Level of education (2008) (baseline = vocational or general secondary school)										
Primary or less (0–8 classes)	-1.9	(1.2)	-1.4	(0.86)	0.0062	(1.0)	-3.2***	(1.1)	0.15	(0.32)
Vocational	-2.0**	(0.92)	-1.6***	(0.52)	-1.3*	(0.67)	-3.6***	(0.93)	0.18	(0.24)
College	-2.1*	(1.1)	-1.4**	(0.70)	-0.94	(0.94)	-2.6**	(1.1)	0.22	(0.30)
University	-4.9***	(1.5)	-3.1***	(0.88)	-1.4	(1.8)	-4.3***	(1.4)	-0.12	(0.39)
Tenure in current job										
First full year	3.8***	(0.60)	2.4***	(0.47)	3.1***	(0.77)			4.3***	(0.64)
Number of years x 10	-0.28	(0.42)	-0.67**	(0.28)	-0.80**	(0.35)			-0.38***	(0.14)
Work experience since leaving school										
Number of years x 10	-7.9***	(1.7)	-6.4***	(1.0)	-9.0***	(2.0)			-2.1***	(0.38)
Squared number of years x 100	1.6***	(0.36)	1.4***	(0.24)	1.8***	(0.44)			0.49***	(0.10)
Type of employment (2008) (baseline = employee)										
Employee of a sole proprietor	4.2*	(2.2)	2.2*	(1.3)	3.6	(2.3)	-0.76	(1.6)	1.6***	(0.61)
Casual worker	72.3***	(5.5)	78.9***	(8.4)	61.5***	(2.6)	76.6***	(15.2)	25.5	(20.0)
Self-employed	4.1*	(2.4)	0.99	(1.2)	1.2	(1.7)	3.3	(2.4)	-0.073	(0.42)
Member of an unincorporated company	-3.5	(2.2)	-1.7	(1.1)	-1.9	(1.6)	-1.4	(1.5)	-0.29	(0.39)
Work schedule (2008)										
Part-time	17.8***	(3.2)	14.6***	(2.8)	20.6***	(2.3)	13.6***	(4.1)	4.0***	(1.1)
Evening, night, weekend work	1.5*	(0.83)	0.93*	(0.53)	1.4**	(0.70)	1.5**	(0.78)	-0.11	(0.20)
Telework	11.6***	(3.4)	6.8***	(2.2)	6.3**	(2.6)	6.7***	(2.4)	0.39	(0.56)

Irregular work pattern	4.1***	(1.4)	2.6***	(0.83)	3.3***	(0.97)	1.8*	(1.0)	0.58	(0.35)
Firm ownership (2008)										
Foreign (more than 50 per cent)	-1.5*	(0.87)	-2.4***	(0.68)	-2.0**	(0.93)	-1.4	(1.6)	-0.76***	(0.25)
Firm size (number of employees, 2008) (baseline = more than 10)										
1	15.7***	(3.1)	12.1***	(2.2)	20.3***	(2.7)	6.7**	(3.2)	2.6***	(0.95)
2–4	1.5	(1.4)	1.7**	(0.78)	2.3*	(1.3)	0.85	(1.5)	0.37	(0.34)
5–10	-1.5	(1.2)	-0.73	(0.65)	-0.84	(0.93)	-2.9**	(1.1)	0.34	(0.32)
does not know (but < 11)	3.3	(4.4)	2.3	(2.3)	2.9	(3.7)	2.8	(4.0)	-0.17	(0.71)
Economic sector (2008) (baseline = industry)										
Agriculture	15.7***	(1.8)	9.9***	(0.96)	8.6***	(2.0)	9.8***	(1.9)	1.1***	(0.43)
Construction	3.3**	(1.7)	2.6***	(1.0)	4.6**	(1.9)	0.29	(1.4)	1.3***	(0.45)
Transportation	20.5***	(2.7)	13.9***	(1.3)	25.0***	(1.3)	15.5***	(2.4)	0.83**	(0.40)
Trade and accommodation	-0.85	(1.0)	0.012	(0.68)	1.4	(1.1)	-1.0	(0.71)	0.21	(0.28)
Services	1.3	(1.2)	1.2	(0.76)	2.2	(1.3)	0.28	(0.94)	0.71**	(0.32)
Education, health, public admin.	3.8***	(1.0)	2.5***	(0.63)	2.5***	(0.95)	3.2***	(0.89)	0.14	(0.21)
Region (2008)										
Micro-regional unemployment rate	18.3**	(7.8)	10.6**	(5.3)	-1.6	(6.6)	16.7**	(6.8)	-1.8	(2.0)
Capital Budapest	6.8***	(2.4)	5.6***	(1.8)	14.6***	(2.9)	6.4**	(3.2)	1.0*	(0.62)
Year (baseline = 2001)										
Year: 2002	0.30	(0.28)	0.13	(0.45)	0.37	(0.48)			-0.057	(0.32)
Year: 2003	-0.033	(0.32)	-0.12	(0.42)	0.15	(0.48)			0.028	(0.34)
Year: 2004	-0.42	(0.35)	-0.42	(0.48)	-0.11	(0.53)			-0.41	(0.30)
Year: 2005	-0.75**	(0.37)	-0.97**	(0.41)	-0.65	(0.47)			-0.50*	(0.29)
Year: 2006	-0.63	(0.41)	-0.63	(0.40)	-0.082	(0.47)			-0.17	(0.29)
									from non-reporting to reporting (equation (8))	
(Average estimated probability)									*35.8*	*(2.7)*
First full year in current job									29.9	(5.0)

Note: see Table 5. For the RE linear model the estimates with cluster-robust standard errors are displayed. Standard errors of average marginal effects for all other models were calculated by bootstrapping the estimated model 1,000 times. For the RE probit models with and without selection the gllapred command of GLLAMM package of Stata was used. Notations for significance: *: p<0.1; **: p<0.05; ***: p<0.01.

4.2 DETERMINANTS OF UNDECLARED WORK

According to Table 5, the models indicate a higher than average ratio and probability of undeclared work where this is expected on the basis of the predictions of theoretical models and everyday experience. After controlling for other variables, males are 3–4 percentage points more likely than females to perform undeclared work, which can possibly be explained by the higher risk aversion of females (Eckel and Grossman 2008). Differences by gender are much larger in permanent than in transitory undeclared work. Undeclared work is more prevalent in situations where the perceived chance of detection is lower, or where information asymmetries between the employer and the employee may be present, e.g. among casual workers (60–80 percentage points more prevalent), part-time workers (15–20 percentage points), people doing telework or working from home (6–12 percentage points) and people with an irregular work pattern (2–4 percentage points). Again, the differences in magnitude are larger in permanent than in transitory non-reporting, and in permanent non-reporting are fairly significant.

Holding everything else fixed, new entrants are 2–4 percentage points more likely to be engaged in undeclared work. This result, as well as the above-average probability of transition to reported work after the first full year of tenure, may be explained by the fact that – according to the LFS – the share of fixed-term contracts is much higher in the first full year (16 per cent) than in subsequent years (less than 3 per cent on average). Hence workers may start a job undeclared, on a fixed-term contract, and later become reported when they switch to an open-ended contract.

Workers in micro-firms, with only a single employee, are about 12–20 percentage points more likely to be unregistered (about 7 percentage points more likely to be permanently undeclared and 3 percentage points more likely to move from the reported to the non-reported state in the transitory regime). The differences between other firm size categories are not significant. The probability of undeclared work in general (and permanent undeclared work in particular) is much higher in agriculture (8–16 percentage points higher) and transport (14–25 percentage points) than in industry, while construction and personal services (education, health care) also show slightly higher probabilities. This last result may be due to the presence of unregistered private teachers and health care professionals. Areas affected by high unemployment (perhaps due to demand-side factors, such as the high ratio of the minimum wage to the average wage) and Budapest (perhaps due to the smaller role of personal interactions) face a significantly greater prevalence of undeclared work. A 1 percentage point higher unemployment rate in a micro-region increases permanent non-reporting by a substantial 0.1–0.2 percentage points. There was no trend visible in the extent of undeclared work between 2001 and 2006.

Holding other factors fixed, undeclared work is most prevalent among people with secondary education. Those with apprentice-based vocational or primary education and college graduates report more working days (1–2 percentage points more), while the figure for university graduates is 3–5 percentage points higher than for comparable people with secondary education. The differences come exclusively from permanent undeclared work, which in all other categories is 3–4 percentage points lower than among those with secondary education; the coefficients for the transitory probability are not significant. Thus education and permanent undeclared work are in a reverse U-shaped relationship. Finally, young people and people near retirement age are significantly more likely to be unreported: the probability of undeclared work is lowest around 25 years after leaving school.

Overall, there is much more heterogeneity in probability in the permanent than in the transitory regime. Explanatory variables that are associated with economic incentives (such as level of education) play a substantially larger role in determining permanent non-reporting, while transitory non-reporting is rather random and is affected by proxies of administrative difficulties and possible negligent behaviour on the part of employees or employers (e.g. part-time or casual workers). In light of this, it is interesting to find that – after controlling for other factors – foreign ownership has a significant negative effect on temporary, but not on permanent undeclared work.

4.3 GOODNESS OF FIT AND LONG-TERM SIMULATIONS

Before simulating long-term scenarios of undeclared work at the individual level, using our two-regime model, we first note that this simple model is indeed able to reproduce the observed patterns of non-reporting in our sample. To show this, using the model we simulated undeclared work scenarios many times for each worker in the sample, and calculated the distribution of the number of undeclared years. Table A2 in the Appendix displays the mean, standard deviation and 5 per cent and 95 per cent quantiles of the simulated ratios of workers who are undeclared for exactly 0, 1, ..., 6 years. All but one of the observed ratios are within the 5 per cent and 95 per cent simulated quantiles, and the remaining case is within the corresponding 1 per cent and 99 per cent quantiles. Not surprisingly, a formal chi-square test does not reject – even at the 10 per cent level – that the observed distribution of undeclared years comes from the model-predicted distribution. Thus the model captures two important patterns – the distinction between permanent and transitory non-reporting and the mild persistence of transitory non-reporting. We also note that the complexity of the model is indeed required to achieve an appropriate fit. For instance, the ratio of 2–5 years of non-reporting would be underestimated if the transition probability from the non-reported to the reported state did not depend on tenure in the current job (first year vs. afterwards).

In our long-term simulations we generate individual undeclared work patterns for ten years because, according to the LFS, a worker spends ten consecutive years on average in the same job, provided she has spent at least two years there. Figure A2 in the Appendix displays the simulated distribution of the number of undeclared years in a ten-year window for workers who were in the sample throughout the period 2001–2006, split by their levels of education (lower than secondary, secondary and tertiary). Although the average time spent undeclared during the ten-year window is 1.0 years for workers with at most secondary education and 0.5 years for those with tertiary education, the differences are substantially larger for permanent non-reporting: 6.1, 7.5 and 2.8 per cent of workers from the three groups are never reported to the authorities in the ten-year simulated window. This illustrates that the long-term burden of undeclared work is more variable across people and socio-economic groups than cross-sectional differences would suggest, because a typical undeclared worker is not sporadically, but rather permanently unreported to the pension authorities.

5. CONCLUSIONS

In this paper we used a unique set of matched administrative and survey data to analyse unreported employment at the individual level in Hungary, with the help of random-effects panel models with endogenous selection and with a two-regime dynamic model.

We found that about 9.5–11 per cent of working time reported in the LFS by permanently employed workers did not appear in the NPID register in 2001–2006. We estimated that only about one-sixth of the discrepancy could be attributed to breaks in work during employment relationships perceived as continuous by the LFS respondents.

The results reinforce the idea that the labour input method advocated in various European countries and at the EU level (GHK/FGB, 2009), can be a simple, yet reliable method for estimating the size and evolution of informal employment, although it tends to overestimate the true magnitude of black work by a few percentage points, since some administrative records are missing for technical reasons.

The estimated effects of individual, firm-specific and regional variables – especially on permanent undeclared work – suggest that non-reporting is a sign of black work, rather than a result of technical failure. Importantly, we observed below-average reporting rates in part-time work, non-standard work patterns, work at home and telework – various forms of ‘atypical employment’ that are gaining ground in European labour markets. Our results on lower reporting rates among males, in small firms and in some sectors such as agriculture roughly coincide with the findings of other studies on undeclared work (e.g. survey-based results in European Commission, 2014, for the EU, and Semjén et al., 2009, for Hungary covering roughly the same period) and on more general forms of tax evasion, such as wage underreporting and envelope wages (Meriküll and Staehr, 2010, for the Baltic states; Elek et al., 2012, for Hungary). Education and undeclared work seem to be in a reverse U-shaped relationship (see Meriküll and Staehr, 2010; Elek et al., 2012; Paulus, 2015, for the effect of education on some other forms of tax evasion).

The findings have clear implications for health care and pension eligibility. Workers whose administrative data are missing (for whatever reason) are only entitled to emergency treatment unless they insure themselves on an individual basis (which rarely happens in Hungary). We found the proportion of such workers to be quite high (about 1 in 10) – even in a sample that excluded employment spells of less than two years.

Expected pensions are also affected by non-reporting, and we could examine this with our panel data. We found that about 6 per cent of workers were permanently undeclared. Across a 40-year labour market career, employees who are unreported for their whole tenure in a job (ten years on average) receive a pension that is about 15 per cent lower than their fully reported counterparts, according to recent Hungarian rules (Pénzügyi tudakozó, 2016). However, people permanently unreported in a ten-year time window have a high probability of being unreported before and after, too; and so their total loss is even higher.

Finally, as a more technical conclusion, we found that explicitly modelling the dynamics of the dependent variable in a panel data setting not only gives greater insight into the data-generating process, but may also yield more efficient parameter estimates than simple panel data methods – in our case, some variables became significant only after permanent and transitory non-reporting were separated.

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Appendix

Table A1

Average non-reporting rates in the estimation sample (per cent)

Non-reporting rate	Unreported days	Unreported dummy	Always unreported	Transitorily unreported*
Average	9.5	9.2	6.6	2.9
Gender				
Male	13.4	13.1	9.6	3.5
Female	5.7	5.4	3.5	2.3
Age (2006 for 'always unreported')				
15–29 years	12.6	11.9	7.4	4.3
30–49 years	9.0	8.8	6.7	2.6
50+ years	9.6	9.4	6.0	3.3
Level of education (2008)				
Primary or less (0–8 classes)	9.2	8.8	6.5	3.1
Apprentice-based vocational	10.3	9.9	7.0	3.3
Vocational or general secondary	10.6	10.4	7.7	2.6
College	6.5	6.4	3.9	2.7
University	5.1	5.0	2.8	2.0
Type of employment relationship (2008)				
Employee	7.0	6.7	4.8	2.2
Employee of a sole proprietor	15.1	14.0	6.7	8.2
Casual worker	90.5	92.9	88.9	50.0
Self-employed	27.6	27.4	21.8	7.2
Member of an unincorporated company	7.7	7.5	4.7	3.2
Occupation (2008, in order of non-reporting)				
Agricultural	38.9	38.4	32.0	9.0
Skilled service workers	27.0	26.8	24.0	3.3
Skilled construction workers	14.1	13.2	8.8	5.2
Porters, guards	13.4	11.9	7.6	4.2
Professionals (except teachers and doctors)	11.4	11.4	7.7	4.0
Elementary	11.3	10.5	7.0	4.3
Drivers	9.8	9.6	6.9	2.3
Skilled blue collars in trade and catering	7.7	7.0	3.2	3.6
Skilled industrial workers	7.5	7.3	4.9	2.6
Administrators	7.2	7.1	5.2	2.7
Technicians	6.3	6.2	5.4	1.4
Cleaners	5.4	5.1	2.6	3.1
Managers	5.0	4.8	1.7	3.2
Office clerks	4.7	4.4	2.4	1.6
Machine operators and assemblers	4.3	3.9	3.4	1.3
Teachers and doctors	2.8	2.6	1.1	1.5
Work schedule (2008)				
Part-time	31.7	30.8	19.8	11.8
Evening, night and weekend work	13.5	13.2	9.5	3.6
Telework	34.8	34.5	27.4	8.4
Irregular work pattern	17.5	17.1	12.7	4.2
Tenure in current job				
First full year	12.9	11.7	-	5.9
More than one year	9.2	9.0	-	2.6
Firm size (number of workers, 2008)				
1	34.8	34.8	28.0	9.4
2–4	12.0	11.4	7.7	4.5
5–10	5.6	5.2	2.4	3.2

does not know (but < 11)	13.7	13.9	8.5	4.8
11 or more	7.2	7.0	5.1	2.2
Firm ownership (2008)				
Domestic (<=50% foreign)	10.4	10.1	7.2	3.2
Foreign (>50% foreign)	3.4	3.0	2.5	1.0
Region (2008)				
Budapest	12.9	12.8	9.3	5.3
Rest of the country	9.4	9.1	6.5	2.8

Note: matched LFS–NPID sample.
Unreported dummy = less than half of the workdays are reported in a given year. The ratio is given as a percentage of the person-years.
Always unreported = never reported during the observed employment spell. The ratio is given as a percentage of the number of workers.
* Transitorily unreported: the average of the unreported dummy for person-years of workers who were reported at least once during their observed employment period.
By definition, the 'always' and 'transitory' columns do not add up exactly to the total column.
All explanatory variables except for age and tenure refer to year 2008 measurements in LFS. They are time-invariant in most cases because the job of the workers did not change during the observed period. For the 'always unreported' dummy, age is categorized according to its 2006 value.
Number of observations: 23,385 person-years covering 4,707 workers.

Table A2

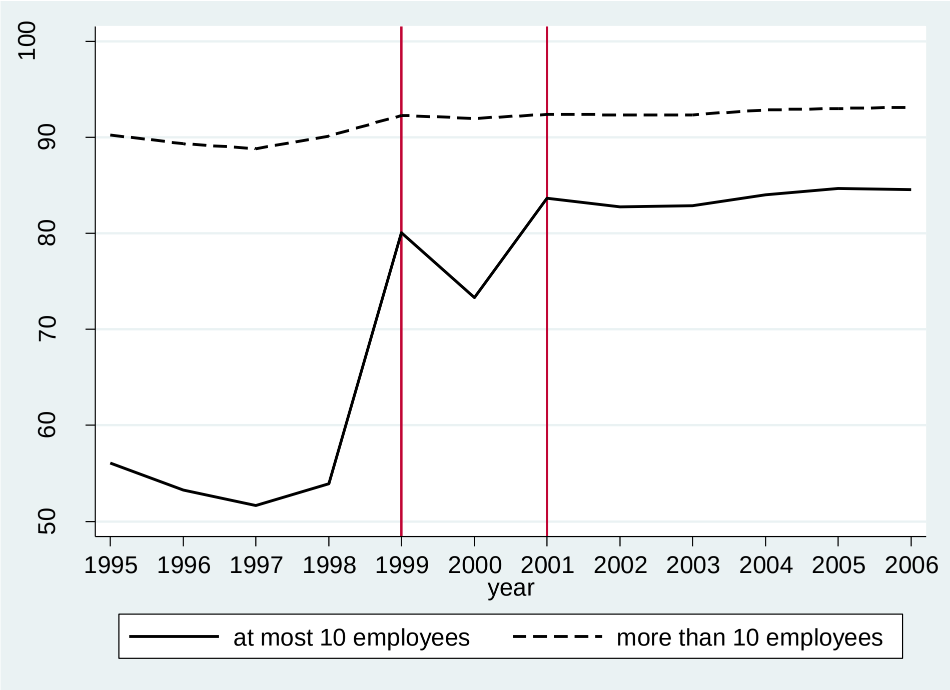
Descriptive statistics of the simulated ratios of workers undeclared for exactly $\boldsymbol{k}$ years ($\boldsymbol{k} = 1, 2, \ldots, 6$) in the six-year period and the observed distribution in the sample (in per cent)

	Number of undeclared years (k)							
Ratios (per cent)	0	1	2	3	4	5	6	Total
Observed	86.41	4.57	1.83	0.89	1.06	0.87	4.38	100.0
Simulated								
Mean	85.73	4.85	2.11	1.29	0.98	0.73	4.31	100.0
S. D.	0.65	0.39	0.23	0.18	0.15	0.12	0.35	
Quantiles								
5%	84.62	4.26	1.74	1.00	0.73	0.57	3.76	
95%	86.84	5.53	2.49	1.60	1.21	0.93	4.91	

Note: simulation of non-reporting dummies based on observed characteristics of 4,707 workers in the matched LFS–NPID sample for 2001–2006, using the two-regime model and taking into account the variance-covariance matrix of its parameter estimates. Number of simulation draws: 1,000.

Figure A1

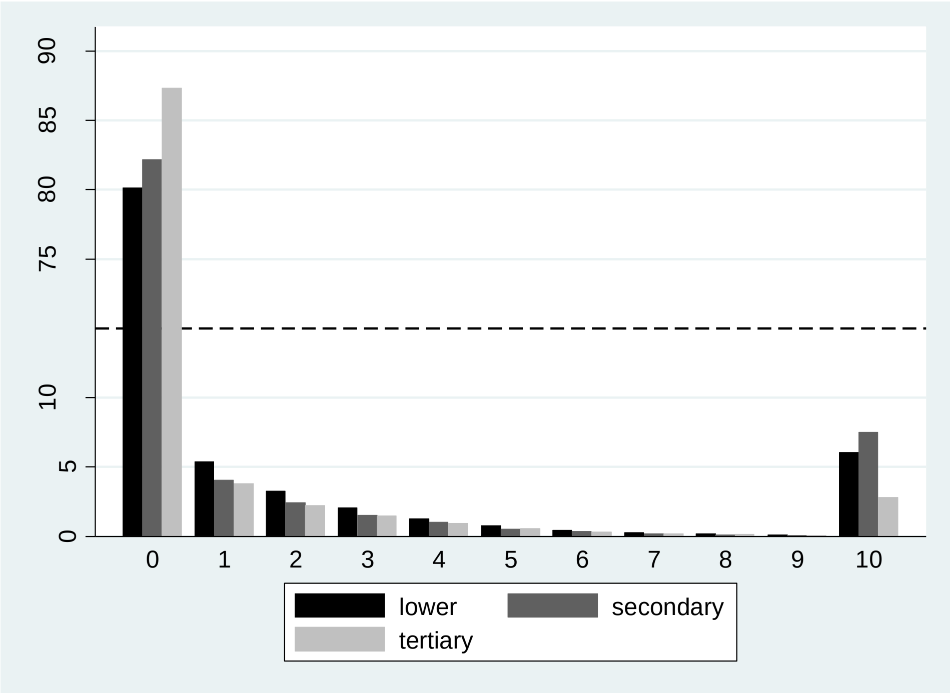
Reporting rates for employees of smaller and larger firms (1995-2006)



Note: matched LFS–NPID sample for 1995–2006. Vertical lines indicate the years of two regulatory changes on NPID reporting. We use data for 2001–2006.

Figure A2

Simulated distribution of the number of unreported years in a ten-year time window



Note: matched LFS–NPID sample. Level of education: lower = primary and apprentice-based vocational, secondary = vocational and general secondary, tertiary = college or university.