Paying for Their Crimes? The Wage Penalty of Incarceration for Ex-Convicts in Hungary

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This paper analyses the effect of incarceration on labour market outcomes and identifies sources of the observed wage penalty from within firm mechanisms. The study estimates a multiple fixed effects panel model on a nationally representative linked employer-employee panel dataset for Hungary, for the period 2003-2011. It is possible to robustly identify the sources of wage penalty for ex-convicts in the data, due to the unique riches of employment history of convicts and their colleagues, and access to firm characteristics. The main model constructs an incarceration-penalty measure as the absolute difference between the post and pre-prison wage disadvantages of convicts compared to the general population. Using this penalty measure it is shown that incarceration hurts the labour market outcomes of even those ex-convicts who find jobs. The within firm analysis of employment spells suggests that the wage penalty comes from convicts working in worse jobs after prison then they did before. This result stays robust across several specifications using matched non-incarcerated control groups and other alternatives. By hiring ex-convicts for low-paid and low-skilled jobs, firms insure themselves against the risk such a hiring could entail. Convicts are willing to accept these offers as facing scarce opportunities they lower their reservation wages. This result suggests a labour market inefficiency caused by asymmetric information: ex-convicts are hired for worse jobs than they are skilled for as firms have no credible knowledge on their trustworthiness. This inefficiency calls for policy action, as low-career prospects on the legitimate labour market push ex-convicts towards crime.

1 Introduction

Prison population has increased substantially in the recent decades across the globe. By the mid-2010s OECD average rose to 147 incarcerated per 100,000 people, with a significant variation in individual countries (OECD, 2016). With the highest incarceration rate of the world, US prison population stood at 672 person out of 100,000 in 2015, while Europe was closer to the OECD average. In Hungary 178 of 100,000 people was in prison in 2015. This proportion fits into Central Eastern European trends and increases ever since (ICPR, 2018). The percentage of incarcerated may appear small, but it does not fully reveal how large part of the society is affected by it. Incarceration rates can be 2-3 times higher for low income groups, minorities and the uneducated (Holzer et al., 2004). Skardhamar (2014) and Bonczar (2003) emphasize that life-time incarceration risks for different segments of society is more informative on the prevalence of the problem. Based on their calculations, an average man until the age 60 has a 11.3% chance of being incarcerated at least once in the US, 6.2% in Norway and 6.9% in Hungary, estimated by Kollo et al. (2018). Based on this metric incarceration already seems more widespread, and it is even more so for disadvantaged groups. Moreover, several studies conclude that incarceration's adverse effects harm not only the convict, but his entire family and social circle. For instance, Dobbie et al. (2018) find a severe intergenerational effect, that parental conviction substantially increases teen crimes and early-life unemployment. Other papers, such as Bhuller et al. (2018), do not find increased criminality but the overall deterioration of families' socio-economic

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status which ultimately worsens the outcomes of children. Even those who are not harmed by crimes and are not connected to incarcerated share the burden of the problem through financing the penitentiary system, reintegration programs and social support for those affected by it Arnold et al. (2018).

Overall, incarceration affects a substantial fraction of society directly or indirectly and it is especially prevalent for low income groups. Statistics show that the majority of crimes are not capital offences with decade long sentences but non-violent thefts and drug related crimes (UNODC, 2018) which are followed by a couple of years in prison. After such sentences convicts are released to be reintegrated into society. The success of this reintegration and escaping recidivism depends crucially on finding a job. A great body of literature discusses the difficulty of this and links post-release unemployment to recidivism (see Grogger (1995), Kling (2006), Holzer (2007), Pager (2003), Cho and Lalonde (2008), Czafit and Köllő (2015), Mueller-Smith (2015) and Bhuller et al. (2016)). Kling (2006), Western et al. (2001) and several other studies find a severe wage loss and deterioration of general job characteristics in the long-run for ex-convicts. However, very few studies identify the source of this wage loss, those firm characteristics and hiring strategies which create the observed post-prison disadvantage. Holzer (2007) and Lundquist et al. (2018) are rare attempts of trying to understand within firm mechanisms and decisions, which ultimately determine ex-convicts labour market outcomes. Holzer (2007) finds strong aversion of hiring ex-convict applicants, especially those with violent crimes, using a small-scale employer questionnaire. Lundquist et al. (2018) assesses the military careers of ex-convicts who were admitted to serve after an extremely thorough screening mechanisms, recommendations and interviews. Both papers have important insights about employer reluctance of risky hires, failed experiments of reintegration but also about successful post-release careers and fast promotions. However, both studies lack the strength to provide general conclusions on specifics of firm decisions which lead to hiring convicts and determine their inferior post-release outcomes. The main analysis of Holzer (2007) uses survey data instead of observed employment spells, while Lundquist et al. (2018) uses detailed observational data but on a very special employer.

This paper aims to fill this gap and explain the post-prison disadvantage by looking into actual within firm dynamics and decisions to hire convicts. To accomplish this, an extremely rich nationally representative linked employer-employee panel of Hungary is used. The data follows 50% of the population monthly, between 2003-2011. 792,944 workplaces are observed including 19,891 firms who hire ex-convicts during the observed time frame. Pre-prison workplaces of convicts and their colleagues during their employment history are also observed. Based on this data it is possible to analyse the characteristics of jobs and firms which absorb ex-convicts, to learn how they are different from the rest of the labour market and the pre-prison workplaces of this population. Analysing these factors helps understanding the determinants of the post-prison penalty.

Several factors and mechanisms could be behind the observed wage-penalty of ex-convicts on the labour market. Hiring ex-convicts is associated with risking damage, stealing or losses attributed to the employees' lower productivity. The latter could stem from the deterioration/no improvement of skills during the incarceration, bad work ethic, bad relationship with co-workers/customers and unexpected quits (see Grogger (1995), Holzer (2007)). Therefore, firms hire ex-convicts less often and it is likely that they try to reduce the risks associated with the hiring and compensate for them. Firms could reduce risk by hiring through more thorough screening, recommendations or by admitting ex-convicts to high-turnover jobs where there is a little chance for them to do harm (Pager, 2003). Compensation for the risky hirings could mean lower wages, short-term jobs for the convicts, or all of these. However, wage-discrimination is prohibited by the law and paying lower wages for the same job within firm could be difficult to maintain. Hiring convicts for the lowest paid, worse jobs at the firm could serve the same purpose in a more subtle way. This can result in worse labour market outcomes for convicts across several dimensions of their jobs after prison. On the employee side, convicts may accept these jobs because of need. It is plausible that facing scarce opportunities after prison they lower their reservation wages and are willing to accept worse jobs than before. To the best of my knowledge no paper has analysed the within firm determinants of incarceration penalty on a large, nationally representative observational data set. From policy point of view it is important to learn about post-prison penalties, their sources and identify whether there is a need for support, as good labour market outcomes are the best defences against recidivism (Chalfin and McCrary (2017)).

This paper analyses the post-prison penalty by identifying the disadvantage of convicts before and after the incarceration compared to the general population. The absolute difference between those coefficients is used as an incarceration penalty measure on labour market outcomes. After identifying this penalty, it is decomposed using several explanatory variables and analysed within firm. It is found that the robust and substantial wage and employment chance penalty after prison comes from hiring dynamics, that convicts work at jobs with worse employment spell characteristics after prison than before. However, within those jobs ex-convicts do not earn less than their never-convicted colleagues. This result persists across several alternative specifications and robustness checks.

This paper presents the analysis as follows. Section 2 introduces the data set and describes its main patterns. Section 3 introduces the identification strategy. Section 4 shows the results of the main specifications, Section 5 includes robustness checks and estimations with alternative control groups; finally, the last section concludes.

2 Data and Descriptive Analysis

2.1 Data

An original data set was constructed for this study using multiple administrative data sources. The core of it is a list of individuals (anonymous IDs) and their basic characteristics received from the National Health Insurance Fund Administration, the Central Administration of National Pension Insurance and the Hungarian State Treasury. It includes information on a random sample of 50% of the population followed monthly during the period 2003-2011. Incarcerated individuals can be identified via a special transfer code in the raw data. This code denotes that the state pays social security contribution after the time people spend in prison.[1] To this skeleton data set, more variables are added from the National Labour Office and the National Tax and Customs Administration. These contain information on employment spells, connect colleagues with each other and add firm characteristics (based on balance sheets and compulsory reported information for filing taxes in Hungary).[2]

This merged data forms a linked employer-employee panel for 2003-2011 which is representative of Hungary. The data is monthly and balanced for each person in it, following 4,601,999 individuals for 108 months. From them 39,825 are observed spending time in prison. The data includes all workplaces where these individuals ever worked at, 792,944 firms in total.[3] 31,293 firms employs ever-convicted individuals before or after their prison spell, 19,891 hires them after the incarceration. This is an extremely large number of observed post-prison employment spells compared to other data sets used in the criminal literature (Chalfin and McCrary, 2017).

[1] Note that it is only known based on the data if a person spends time in prison. It is unknown, whether it is actual time served, pre-trial detention served in prison (possibly without a conviction) or other sort of detention. For short sentences the latter two options are likely. In Hungary there is no legal maximum for time spent in pre-trial detention but indications for keeping it as short as possible (Fazekas et al., 2015). This makes it difficult to tell these spells apart from actual sentences. Since it is also possible to receive a criminal record without having to serve time in prison (beside the pre-trial detention), some of these spells are viewed the same way on the labour market as actual sentenced time. It has also become a common practice towards the end of the observed period for the poorest of the society, to serve time in prison instead of paying fines (for minor thefts and parking violations etc.) (Janecsko, 2013). This again, cannot be identified in the data, but the shortest of spells most likely fall into this category.

[2] This merged dataset "AdminII", is available to me from the courtesy of the Databank of the Economics Institute of the Hungarian Academy of Sciences and is used with their permission (for more information contact Janos Kollo: kollo@econ.core.hu).

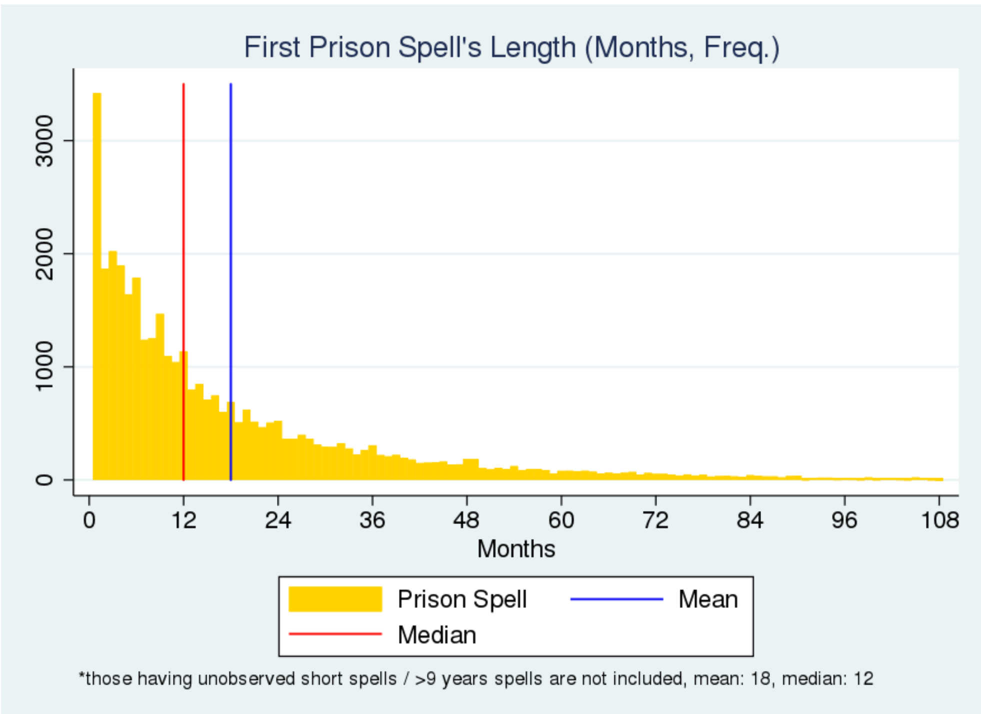
[3] Note that the data is not balanced at the firm level: firms are observed as long as at least one individual works at them at any given month.

Table 1: People, Prison and Employment

	Number	Percent
Total	4601999	100.00
Non-Convict	4562174	99.13
Convict	39825	0.87
Number of prison spells:		
1 prison spell	28847	72.43
More prison spells	10978	27.57
Prison spell length (first):		
<6 months	5673	14.24
>=3 & <6 months	6080	15.27
>=half & <1 year	8697	21.84
>=1 & <3 years	13488	33.87
>=3 years	5887	14.78
Censored (first):		
Observed before & after	23867	59.93
Observed only before	8052	20.22
Observed only after	7479	18.78
Always in prison	427	1.07
Employment Before & After Prison (first):		
Works before & after	6445	16.18
Works only before	8184	20.55
Works only after	10645	26.73
Never works	14551	36.53

Notes: This table includes the number of observed individuals by group in the data. The information on sentence lengths, censoring and employment is related to the first observed prison spell of each convict. Some convicts, especially those with shorter spells go back to prison multiple times. Statistics on the first spell are presented here, as in further analysis convicts' outcomes are assessed in relation to their first observed prison spell.

Figure 1: Time in Prison



Notes: This figure shows the length of the first observed prison spell of convicts during 2003-2011 measured in months. A person is considered to be in prison if a person is in prison on the 15^{th} of the month. Spells too short to include the 15^{th} of any month are not recorded in the data.

The data has variables on basic personal characteristics (sex, age, education (approximate), health expenditure, social allowances (care, disability)), local labour market attributes based on reported address (unemployment rate, proportion of Roma population), employment spell specifics (wage, length, number of days worked in a month, occupation, employment contract type) and firm characteristics (size, industry, revenue, value added, K/L ratio, export %). Monthly variables are reported based on their values on the 15^{th} of each month. All variables recorded in Hugarian Forints (HUF) are transformed to real values using a monthly chained CPI (Hungarian National Bank, 2015) and are winsorized at the bottom 1^{st} and top 99^{th} percentiles to correct outlier data errors.

This data set has several advantages and disadvantages compared to others used to analyse the effect of incarceration. This data is completely unique in being representative, following convicts both before and after incarceration for a long time, having information on their colleagues' employment history and detailed information on the firm. All of this is measured with no attrition an minimal measurement error, as this information is used to form bases for taxes and transfer payments. It is extremely rare world-wide to have observed data on the employment spells of ex-convicts at 19,891 different firms along with the full employment histories of their never-convicted colleagues. The fact that never-incarcerated colleagues and firms who do not hire convicts are observed in the same data set provides a unique opportunity. It is possible to analyse what distinguishes firms who hire convicts, how convicts differ from their colleagues and how their employment spell characteristics change after prison. Information on firm characteristics and performance measures is extremely uncommon in the criminal literature and adds more depth to this analysis. Most studies have access to non-representative surveys on convicts and their workplaces after prison and have no information on their colleagues. Most are richer in personal characteristics but do not include detailed pre-prison data on subsequent workplaces (see Bhuller et al. (2016), Aizer and Doyle (2015) or Bayer et al. (2009)).

On the other hand, it is a limitation that this data set does not include information on the type of crime committed, the time spent in pre-trial detention, specifics on the conviction process (judge selection) and whether a person is released with probation. These factors are shown to be important determinants of the post-prison outcomes. Many studies analyse how judge selection and plea negotiation affects sentence length and reintegration (see Bhuller et al. (2016), Aizer and Doyle (2015), Dobbie et al. (2018)). Other studies find that employment chances can be very different conditional on the type of crime, which information is in some countries accessible for employers during the hiring process (see Pager et al. (2009), Pager (2003), Holzer et al. (2004), Holzer et al. (2006) Harris and Keller (2005)).[4] These missing pieces information makes this data set unsuitable to study some of the usual questions the criminal literature asks, but its unique richness of observed ex-convict employment spells, firms and colleagues opens up other areas to research. Namely, it allows analysing how within firm dynamics drive the labour market outcomes of ex-convicts. The limited data on the crime and the person paired with rich firm level information make this data similar to the ones used in displacement studies or in those analysing the effect of other disruptions in career (such as Jacobson et al. (1993), Abowd et al. (1999) and Couch and Placzek (2010)). This implies that the identification strategy will draw on their methods rather than the ones used in the criminal literature.

2.2 Descriptives

Table 1 describes the most basic facts about individuals in the data. Most importantly, that out of a large number of observed individuals, 4,601,999, less than one percent is observed spending time in prison, only 38,925 people. Most of them are non-recidivists (72.4%) and spend relatively short time in prison. About half of the convicts spend at most a year in prison on their first observed sentence and less than 15% serves for longer than 3 years. Figure 1 shows the full distribution of prison spell lengths restating the dominance of short spells.

[4]In Hungary any firm can ask for criminal record and it is compulsory for some public institutions. It is either clean or not, and does not include the crime. Criminal records are automatically cleared after 3 years post-release for sentences <1 year, after 5 years for 1-5 year, after 8 years for 5-10 year and after 10 years for longer sentences (Meszaros and Csaki, 2012).

Naturally, as the data covers only the 2003-2011 period, thus some convicts have censored prison spells and are only observed before or after their incarceration. Table 1 shows that approximately 60% of all convicts have observed outcomes for both before and after prison. Note, that it is possible that some of the convicts and even the non-convicts had a prison spell prior to this observed period. This unobserved criminal past already influences the outcomes for some of the sample, thus its effect is tested as a robustness check(Section 5.3).[5] It is important to see that not all of those observed before and after incarceration work in both time frames. In fact, only about 16.6% percent of all convicts are observed working both before and after their prison spell.

Table 2 gives a more detailed summary on how convicts and the general population differ in terms of the main variables in the data. Additionally, the table separates the typical characteristics of convicts before and after their first prison spell. As expected, the difference is radical between convicts and the general population. Convicts are on average younger, predominantly male and live in slightly worse off areas. They have lower qualifications and work in occupations requiring less skills. They are employed for shorter spells, less often work full months and connected to all of these factors, they earn less. On average convicts work for larger firms with less revenue and value added. The health related variables show that the general population spends more on health issues than convicts do and are granted allowances more often, which may seem unexpected at a first glance. However, this does not necessarily mean that the general population is of poorer health. Higher health expenditures could be related to their higher average age and but also to better access and more means to spend on their health.[6] Care allowance is awarded when a family member, sick relative or child needs support. Although, we don't have information on family ties it is plausible that younger, male convicts are less likely to have family members to care for than the general population.

The difference between convicts' before and after prison periods are smaller relative to the previous gap, but it is present. After prison convicts earn less, work in slightly shorter employment spells and in jobs requiring less skills than before. These raw numbers already show that their status worsens. Note that these differences may seem small, but as convicts are at the bottom of the earnings distribution even small difference in the earnings means large differences in the living standards.

Figure 2 shows the entire distribution of monthly real wages for the general population and convicts before and after prison. This graph shows the raw data, without any adjustment for compositional differences or other factors. Again, the main difference in the wage seems to be between the general population and convicts. For convicts, the right tail of the wage distribution is very thin while there is a lot of weight on the low-wage left-tail. This is fully expected as the composition of the two groups are entirely different in terms of education and most other characteristics. In further analysis this compositional difference is eliminated and convicts' wages are compared to their most similar counterparts from the general population. The distributions of wages before and after prison are not radically differently shaped, however, there is a difference between their means and medians. It is worth restating that at low wage levels even small differences matter.[7]

[5]The data is constructed in a way that the start date of all left-censored prison spells is known and the end date of right-censored spells is recorded as long as they finish until the end of 2013.

[6]The health expenditure variable captures the total amount the state healthcare system spends on each individual in a given year, including hospital stays and state supported medicines. Although, the reported amounts are paid by the state differences in access and the co-payment for medicine could result in higher amounts for those better off.

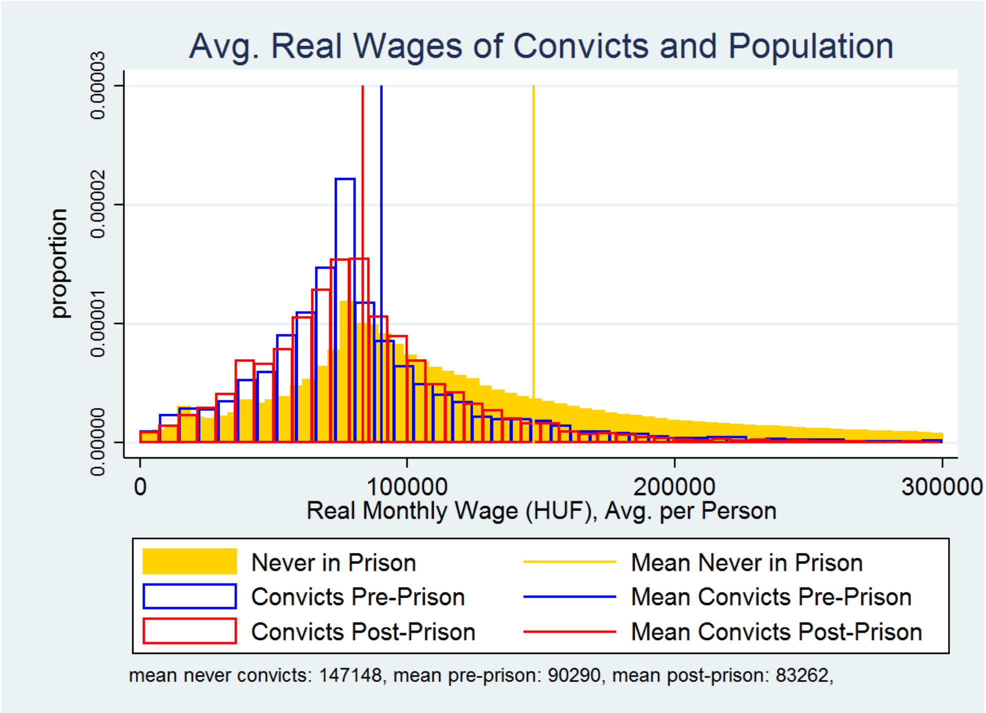
[7]Note that it is an anecdotal common practice of evading taxes on the low wage labour markets of Hungary that employees are reported earning minimum wages, but they receive the rest of their wage in cash. This could result in low variance at the lower tails of the distribution, but fortunately the distribution presented here does show such a peak.

Table 2: Descriptives of People

mean/p50/sd	Never in Prison	Ever in Prison	Before Prison	After Prison
Age	41.82	33.94	30.86	36.68
	41.08	32.67	29.54	35.18
	(18.70)	(11.30)	(11.25)	(10.77)
Male	0.48	0.91	0.91	0.92
	0.00	1.00	1.00	1.00
	(0.50)	(0.28)	(0.29)	(0.27)
Regional Unemployment Rate	0.08	0.09	0.07	0.10
	0.07	0.09	0.07	0.10
	(0.02)	(0.03)	(0.02)	(0.03)
Roma Proportion on Zip Code Address	0.03	0.03	0.03	0.03
	0.02	0.02	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Receives Disability Pension	0.09	0.04	0.03	0.04
	0.00	0.00	0.00	0.00
	(0.26)	(0.17)	(0.16)	(0.18)
Receives Care Allowance	0.04	0.03	0.03	0.03
	0.00	0.00	0.00	0.00
	(0.14)	(0.11)	(0.14)	(0.13)
Real Health Expenditure per Year	101811.55	55268.49	54980.65	60069.58
	40790.44	16802.75	10124.17	9884.98
	(155781.06)	(107467.43)	(133634.99)	(136044.88)
Schooling (Approx.)*	1.80	1.31	1.37	1.29
	2.00	1.00	1.00	1.00
	(1.62)	(1.33)	(1.34)	(1.30)
Number of Firms	2.54	2.30	2.29	2.45
	2.00	2.00	2.00	2.00
	(1.80)	(2.15)	(1.82)	(1.81)
Number of Employment Spells	3.14	3.63	3.74	3.03
	2.00	3.00	2.00	2.00
	(2.45)	(2.76)	(2.33)	(2.38)
Monthly Real Wage (HUF)	147147.75	88174.28	90290.28	83262.22
	100604.24	73862.11	74983.45	73784.75
	(125474.56)	(55369.44)	(70013.62)	(48104.80)
Days Worked/Month	28.61	26.41	27.01	26.18
	30.27	28.32	29.03	28.44
	(3.96)	(5.13)	(4.94)	(5.59)
Completed Tenure (Months)	14.92	6.73	6.72	6.15
	9.88	6.13	6.14	6.09
	(15.46)	(8.27)	(8.80)	(7.98)
Occupation*	5.42	6.05	5.84	6.04
	5.00	7.00	6.00	7.00
	(1.98)	(1.58)	(1.75)	(1.66)
Size	583.94	776.91	591.80	785.84
	42.00	35.57	29.70	42.46
	(115.82)	(136.19)	(12076.04)	(15013.61)
Real Firm Revenue (1000 HUF)	27841.97	20790.38	23020.59	19345.15
	13467.48	10142.66	10743.12	9154.68
	(176320.44)	(91836.92)	(92995.64)	(84053.92)
Real Firm Value Added	11650476.84	3621899.94	5327416.03	2498947.56
	306302.22	147563.81	174999.58	90665.41
	(44414143.31)	(15403869.17)	(21558114.35)	(12333631.88)
Firm Capital to Labour Ratio (K/L) (Real HUF)	7553.95	4766.04	4759.18	4917.28
	2856.26	2038.00	2049.14	1820.60
	(64937.82)	(12730.30)	(14952.49)	(14832.34)
Firm Export Share	0.21	0.21	0.18	0.27
	0.03	0.04	0.00	0.10
	(0.30)	(0.29)	(0.28)	(0.32)
Proportion of Thosw Who Never Works	0.35	0.37	0.34	0.39

Notes: This table shows the average, median and standard deviation of the variables collapsed to a person id level first. For most variables the mean of the variable per person was calculated during the collapse. For Schooling, Occupation the mode per person was used (based on employment spells). Schooling is an approximate measure created based on the skill requirement of all employment spells of a given individual.Occupation is formed based on the same classification in line with ISCO-8 standards. Their central tendencies: Schooling: 1=no education: only unskilled jobs, 2=some technical education (likely no high school diploma): max. low-skilled blue-collar jobs: e.g.: machine operator. Occupation: 5 = Skilled Blue Collar Job, 6 = Low-Skilled Blue Collar Job, 7 = Unskilled/No Education Job. The proportion of those who never work is just a share without any distribution.

Figure 2: Monthly Real Wages of the General Population and Convicts Before or After Their Sentence



Notes: This figure shows the monthly real wages of those who worked at least once during 2003-2011, when they worked. Wages above 300,000 (90th percentile of general population) are not shown for better visibility.

Tables 3 to 10 focus on change in the employment spell characteristics of convicts before and after prison. The tables help explaining whether convicts transition into lower paying jobs after prison that are systematically different from their pre-prison ones in several aspects.

Table 3 shows whether there is a transition from higher to lower paying jobs after the incarceration. The lines of the table show the post-prison wage distribution by pre-prison wage percentiles. The first row shows that from convicts whose average wages fell into the bottom 10% of the wage distribution before prison, how large fraction has post-prison wages in the bottom 10%, 10-25%, 25-50% etc. percentiles of the overall wage distribution. The second row describes the post-prison wage distribution of those who on average earned in the 10-25% of the wage distribution pre-prison. The rest of the rows follow the same logic. In each row the first column shows the proportion of convicts in the given wage percentile category before prison. The table has separate rows and columns for those who are observed only pre/post-prison and for those who are observed, but do not work pre/post prison.

Overall, Table 3 tells whether convicts keep their position in the wage distribution or transition to lower wage percentiles or to unemployment after prison. The first important conclusion is that even before prison the majority of convicts do not work and those who work fall into low percentiles of the wage distribution. Second, Table 3 clearly shows transitioning to lower percentiles of the wage distribution after prison: from any pre-prison wage percentile category the majority fall into the bottom 25% of the wage distribution post-prison. The rest of the transition tables, Table 4 to 10, follow the same logic and analyse factors which can be determinants of the emerging post-prison wage penalty.

Table 4 to Table 6 focus on the ***employment spell characteristics*** and show whether different jobs are behind the lower post-prison wages. Table 4, analysing occupational transitions, shows that most convicts worked in blue collar and unskilled positions before prison. After prison unskilled jobs gain a strong dominance, showing a downwards shift in the occupation hierarchy for convicts. As jobs requiring less skills pay lower wages this could partly explain the downward shift in the wage distribution. Wage losses could also stem from merely the change of occupation, losing the wage premium of occupation-specific knowledge (Jacobson et al., 1993).

Table 5 shows the changes in employment spell length before and after incarceration. Longer employment spells tend to have higher average wages, as usually with tenure wages grow and longer spells fall under better protected non-temporary work contracts. This table shows that convicts typically have very short employment spells even before prison, with a median length of less than a year.[8] After prison an even higher percent of convicts work in the shortest spell category than before. Many convicts who were not observed working before prison will enter to these jobs and many fail to hold on to as long spells as they did before prison. However, the change here seems less substantial than the one for occupations.

Table 6 shows the transitions based on the employment contract type. The type of contract is expected to be related to both the employment spell length and wages. Short spells could fall under temporary job contracts, typically seasonal employment with low wages. However, Table 6 displaying the contract type variable in the data does not confirm the expectations. It suggests that regular contracts are the most widespread both before prison and after prison, gaining even more prevalence in the post-prison period. The table also shows that public sector employment falls substantially after prison, as those jobs have strict criminal record checks required by law (Meszaros and Csaki, 2012). Because of the small weight of other employment contracts types than the regular this variable will not be able to substantially explain the post-prison wage penalty.

Table 7 to 10 focus on the ***characteristics of the firms*** convicts work for before and after prison and show whether differences in them are behind the lower post-prison wages. Table 7 shows the transitions by firm industries. Some sectors could be better paid than others as they require different tasks and skills. Table 7 show that convicts predominantly worked for manufacturing firms and small family enterprises before prison.[9] After prison, besides manufacturing, the construction sector absorbs most of the working convicts with followed by the retail-trade sector. This latter presumably means warehouse jobs or even security positions. All of these sectors offer plenty of jobs in which hiring convicts poses relatively small risk: unskilled positions, short-term jobs with high turnover, positions without contact with customers and jobs where no expensive and easy to damage machinery is used. A priori it is not obvious why post-prison sectors would pay lower wages in general, than manufacturing. However, it could be related to the kind of jobs these sectors hire ex-convicts for.

Table 8 shows whether firm sizes are different for convicts before and after prison. Gibson and Stillman (2009) and other studies show that larger firms often pay higher wages, as they could be more productive due to higher specialization. This table shows that mostly the smallest and the largest firms employ convicts both before and after prison with a little change in their proportions. This change does not seem to be strong enough to explain the wage-penalty for ex-convicts; however, it tells an interesting story. Convicts are hired by large and high turnover firms presumably those who can afford themselves to hire some risky workers. They work for small family businesses where their social ties presumably matter more than their criminal past. In general, middle sized firms are the least represented as post-prison employers. Table 9 and Table 10 studies transition in the firm revenue and capital per employee distribution. The tables have similar conclusions. Convicts work for firms with low revenue and capital intensity before prison and slightly increasingly so after prison. However, it is difficult to tell whether these small shifts are behind substantial post-prison wage penalty.

Overall, this descriptive section established some of the main facts about convicts and their labour

[8] Note that some of the convicts are observed only for a short time period before their incarceration, which limit how long their employment spells could be, in contrast to the general population. The same applies to their post-prison periods too.

[9] Micro-enterprises and family businesses are not required to report detailed firm-information when filing taxes including their industry of production

market position. The presented statistics show that the convict population is small and has a severe disadvantage in almost all domains compared to the general population. There is a substantial downward shift in wages in the post-prison period compared to pre-prison earnings. This shift seems to be driven mostly by occupational and industry transitions, and partly, by getting employed by lower quality firms after the incarceration. However, these statistics are still descriptive and it calls for regressions to confirm the importance of these factors.

Table 3: Transition in the Monthly Real Wage Distribution Before and After Prison

BEFORE\AFTER	**PRE** %	<10% %	10-25% %	25-50% %	50-75% %	75-90% %	90%< %	A. %	B. %	Total %
<10% real wage	**25.87**	**22.021**	10.071	5.525	1.263	0.142	0.032	39.653	21.294	100.00
10-25% real wage	**18.84**	22.285	**14.115**	7.372	2.394	0.273	0.042	33.438	20.080	100.00
25-50% real wage	**8.76**	21.329	12.020	**10.890**	3.931	0.362	0.090	33.077	18.301	100.00
50-75% real wage	**3.47**	19.954	11.174	12.657	**6.613**	0.798	0.342	32.155	16.306	100.00
75-90% real wage	**1.05**	19.925	8.647	13.534	10.526	**3.008**	0.376	28.195	15.789	100.00
90%<real wage	**0.70**	11.299	10.734	6.780	6.215	3.390	**7.345**	38.983	15.254	100.00
A. person not observed	**17.00**	48.720	31.215	15.596	3.794	0.559	0.116	**0.000**	0.000	100.00
B. person observed, no work	**25.12**	53.441	28.225	13.577	3.985	0.583	0.189	0.000	**0.000**	100.00
Total	**100.00**	**34.272**	**19.186**	**10.418**	**3.142**	**0.443**	**0.158**	**20.820**	**11.561**	**100.00**

Notes: This table is formed the in following way: for all employment spells before and after prison the average monthly real wage by spell is taken. Then the average of those wages is considered separately for the before and the after prison period, and classified to the given wage percentile ranges of the overall wage distribution. Then the distribution of the after prison wage percentiles is plotted by the before prison percentiles.

Table 4: Transition Between Occupations Before and After Prison

BEFORE\AFTER	**PRE** %	1. %	2. %	3. %	4. %	5. %	6. %	7. %	8. %	9. %	A. %	B. %	Total %
1. - Top Manager	**1.26**	**14.89**	9.06	3.88	3.56	5.83	2.26	1.94	0.00	3.24	39.16	16.18	100.00
2. - Other Manager	**2.39**	3.06	**19.18**	2.38	6.96	6.96	2.72	2.55	0.17	2.55	35.65	17.83	100.00
3. - Professional	**1.09**	1.50	5.69	**14.29**	8.27	3.76	4.51	3.38	0.38	3.76	39.47	15.04	100.00
4. - Other White Collar	**3.51**	1.95	2.64	2.29	**16.63**	9.98	4.36	5.85	0.00	2.75	37.16	16.40	100.00
5. - Skilled Blue Collar	**18.41**	0.42	0.86	0.40	1.68	**22.01**	4.57	14.47	0.00	3.73	32.02	19.84	100.00
6. - Low-Skilled Blue Collar	**7.00**	0.23	0.75	0.17	1.09	9.84	**21.29**	14.15	0.00	3.22	31.53	17.72	100.00
7. - Unskilled Laborer	**19.98**	0.18	0.28	0.08	0.43	6.35	2.53	**26.50**	0.00	2.79	38.54	22.31	100.00
8. - Other: religious, NGO	**0.21**	5.41	5.41	8.11	2.71	0.00	0.00	8.11	**13.51**	0.00	35.14	21.62	100.00
9. - Missing: entrepreneurs	**4.25**	1.11	1.63	0.67	2.08	10.01	2.22	10.01	0.00	**8.97**	43.51	19.79	100.00
A. person not observed	**17.00**	1.40	2.75	1.16	4.10	27.98	10.87	44.86	0.5	6.84	**0.00**	0.00	100.00
B. person observed, no work	**25.12**	1.79	2.99	1.18	4.85	24.34	9.10	46.12	0.03	9.59	0.00	**0.00**	100.00
Total	**100.00**	**1.22**	**2.28**	**0.97**	**3.36**	**17.88**	**7.32**	**28.82**	**0.04**	**5.72**	**20.82**	**11.56**	**100.00**

Notes: This table is formed the in following way: for all employment spells before and after prison the mode of occupations was taken. The mode of those occupations is considered separately for the before and the after prison period. Then the distribution of the after prison occupations is plotted by the before prison occupations. Occupation could change within employment spells and is measured by a categorical, ISCO-8 compatible variable.

Table 5: Transition in the Employment Spell Length Distribution Before and After Prison

BEFORE\AFTER	**PRE** %	<=1 %	1-3 %	3-6 %	6-12 %	12-24 %	24+ %	A. %	B. %	Total %
1 month max.	**25.98**	**15.79**	11.92	4.10	2.06	0.72	0.26	39.83	21.99	100.00
1-3 months	**14.88**	15.82	**13.09**	5.51	2.90	1.22	0.48	37.29	20.53	100.00
3-6 months	**7.06**	15.25	11.94	**4.54**	4.76	1.63	0.841	37.500	20.01	100.00
6-12 months	**5.49**	13.63	10.09	5.70	**5.12**	2.24	1.51	38.57	16.94	100.00
12-24 months	**2.73**	11.16	8.55	5.94	6.67	**3.91**	2.03	34.06	17.97	100.00
24+ months	**1.73**	7.08	8.45	4.34	5.02	2.51	**2.28**	46.12	15.30	100.00
A. person not observed	**17.00**	36.24	29.21	12.97	9.92	4.96	3.10	**0.00**	0.00	100.00
B. person observed, no work	**25.52**	37.50	29.08	13.04	8.44	4.05	1.83	0.00	**0.00**	100.00
Total	**100.00**	**24.23**	**19.23**	**8.55**	**6.09**	**2.93**	**1.71**	**20.82**	**11.56**	**100.00**

Notes: This table is formed the in following way: for all employment spells before and after prison the length of employment spell is taken, measured in months. The mean of those spell lengths is calculated separately for the pre- and post- prison period, categorized as shown in the table. Then the distribution of the after prison employment spell lengths is plotted by the before prison occupations.

Table 6: Transition Between Employment Contract Types Before and After Prison

BEFORE\AFTER	**PRE** %	1. %	2. %	3. %	4. %	5. %	6. %	A. %	B. %	Total %
1. - Employment Contract	**46.64**	**39.91**	0.21	0.82	2.64	1.06	0.01	35.20	20.16	100.00
2. - Public Sector	**1.87**	35.59	**5.72**	0.00	1.70	1.91	0.00	40.89	14.20	100.00
3. - Public Work Program*	**0.08**	0.00	0.00	**0.00**	0.00	0.00	0.00	100.00	0.00	100.00
4. - Temporary Contract	**1.63**	22.03	0.24	0.97	**6.78**	0.73	0.00	50.61	18.64	100.00
5. - Entrepreneur	**3.35**	28.84	0.24	0.12	1.54	**17.49**	0.00	30.38	21.40	100.00
6. - Missing, Unclassified	**1.31**	24.47	0.00	0.00	0.91	0.00	**3.63**	50.45	20.54	100.00
A. person not observed	**17.00**	91.13	0.51	0.70	4.59	3.07	0.00	**0.00**	0.00	100.00
B. person observed, no work	**25.52**	86.71	0.47	1.50	7.07	3.83	0.43	0.00	**0.00**	100.00
Total	**100.00**	**59.39**	**0.43**	**0.92**	**4.07**	**2.64**	**0.16**	**20.82**	**11.56**	**100.00**

Notes: This table is formed the in following way: based on all employment spells the mode of employment contract types is calculated separately for the pre- and post-prison period. Then the distribution of the after prison employment contract types is plotted by the before prison contract types. Each employment spell is only included with one value, there is no weighting based on the length of the spell. Employment contract type does not change during an employment spell. * Public Work programs are only available in 2011.

Table 7: Transition Between Industries Before and After Prison

BEFORE\AFTER	PRE %	A %	B %	C %	DE %	F %	G %	H %	I %	K %	L %	MJ %	OPQR %	PO %	Q %	1. %	2. %	3. %	Total %
A - agriculture	**2.17**	**11.81**	0.00	5.70	0.95	3.96	2.69	2.22	0.45	0.00	0.48	0.00	0.16	4.12	2.53	4.91	40.19	18.83	100.00
B - mining	**0.11**	3.33	**3.33**	23.33	0.00	3.33	3.33	3.33	3.33	0.00	0.00	0.00	0.00	3.33	6.67	6.67	23.33	16.67	100.00
C - manufacturing	**11.61**	1.82	0.00	**18.57**	1.36	5.86	2.87	0.96	1.11	0.12	0.74	0.22	0.43	4.13	6.32	3.61	32.63	19.25	100.00
DE - electricity, water	**1.65**	0.44	0.22	4.62	**15.17**	4.40	0.66	0.88	0.66	0.00	3.96	0.00	1.32	4.40	3.08	2.42	29.45	28.35	100.00
F - construction	**5.61**	1.97	0.00	5.53	0.92	**17.88**	2.52	0.55	0.80	0.12	0.80	0.18	0.49	3.38	4.36	4.36	35.26	20.89	100.00
G - trade	**5.37**	1.46	0.13	6.94	0.53	3.640	**17.99**	2.32	1.72	0.07	0.99	0.07	0.40	1.46	4.23	3.31	36.37	18.39	100.00
H - transportation	**2.17**	0.68	0.34	6.60	0.85	3.38	5.25	**19.12**	1.52	0.00	0.85	0.17	0.17	3.22	3.55	4.06	31.64	18.61	100.00
I - accomodation	**1.59**	0.69	0.23	5.75	0.69	2.53	6.90	1.15	**17.70**	0.00	1.15	0.23	0.69	2.30	4.83	2.99	30.81	21.38	100.00
K - finance	**0.27**	1.24	0.00	1.24	0.00	3.70	11.11	1.24	2.47	**12.35**	1.24	0.00	1.24	2.47	3.70	4.94	41.98	11.11	100.00
L - real estate	**0.99**	1.47	0.00	5.50	0.73	8.10	4.76	0.37	1.10	0.00	**12.82**	0.00	0.37	2.56	2.56	4.40	35.16	20.15	100.00
MJ - IT	**0.21**	0.00	0.00	3.33	0.00	1.67	6.67	1.67	0.00	0.00	0.00	**13.33**	1.67	1.67	11.67	8.33	38.33	11.67	100.00
OPQR- public sector	**1.67**	1.76	0.00	2.20	0.88	7.41	4.19	0.88	2.42	0.00	0.22	0.00	**5.95**	3.17	3.52	1.10	43.83	22.47	100.00
Q - other industry	**0.12**	1.51	0.04	3.30	0.78	2.69	2.16	0.94	0.49	0.25	0.33	0.04	0.73	**18.11**	2.04	6.49	42.05	18.07	100.00
PO - public other	**1.37**	1.99	0.07	7.18	0.55	3.83	3.49	1.16	1.30	0.48	1.10	0.21	0.89	3.49	**12.25**	3.22	38.74	20.06	100.00
1. missing: micro firm	**19.37**	1.66	0.08	6.12	1.59	5.44	4.46	1.66	1.59	0.23	1.51	0.15	0.53	3.78	3.40	**12.62**	31.37	23.81	100.00
2. person not observed	**17.00**	5.54	0.14	20.28	3.89	13.87	9.22	3.73	3.00	0.21	2.40	0.26	1.51	18.76	10.08	7.12	**0.00**	0.00	100.00
3. observed, no work	**25.12**	5.17	0.11	15.85	3.61	14.13	9.06	2.88	3.54	0.35	2.79	0.35	2.05	17.26	11.01	11.86	0.00	**0.00**	100.00
Total	**100.00**	**7.37**	**0.09**	**12.25**	**2.37**	**11.28**	**6.60**	**2.47**	**2.33**	**0.25**	**1.76**	**0.24**	**1.20**	**5.04**	**7.33**	**7.03**	**20.82**	**11.56**	**100.00**

Notes: This table is formed the in following way: for all employment spells before and after prison the mode of firm industries was taken. The mode of those industries is considered separately for the before and the after prison period. Then the distribution of the after prison industries is plotted by the before prison industries. A firm's industry could change within employment spells and is measured by an NACE-1 level industries. For the better visibility some of the industries are grouped together.

Table 8: Transition Between Firm Size Categories Before and After Prison

BEFORE\AFTER	**PRE** %	0-10 %	10-50 %	50-250 %	250+ %	A. %	B. %	Total %
0-10 employees	**15.53**	**27.31**	8.96	3.07	6.48	34.88	19.30	100.00
10-50 employees	**11.17**	13.50	**15.06**	6.45	12.22	31.67	21.11	100.00
50-250 employees	**9.19**	8.05	10.25	**10.33**	16.32	33.96	21.09	100.00
250+ employees	**22.20**	6.04	6.25	5.81	**22.77**	39.72	19.41	100.00
A. person not observed	**17.00**	25.21	21.16	13.69	39.94	**0.00**	0.00	100.00
B. person observed, no work	**25.12**	28.21	18.70	13.94	39.16	0.00	**0.00**	100.00
Total	**100.00**	**19.14**	**13.68**	**9.26**	**25.54**	**20.82**	**11.56**	**100.00**

Notes: This table is formed the in following way: for all employment spells before and after prison the average firm size by spell is taken. Then the average of those sizes is considered separately for the before and the after prison period, and is categorized as shown in the table. Then the distribution of the after prison wage percentiles is plotted by the before prison percentiles

Table 9: Transition in the Firm Revenue Distribution Before and After Prison

BEFORE\AFTER	**PRE** %	<5% %	5%- 25% %	25%- 50% %	50%- 75% %	75%- 95% %	95% %	Missing %	A. %	B. %	Total
<5% revenue firm	**5.96**	**10.68**	8.03	4.18	2.59	1.00	0.46	9.03	42.54	21.50	100.00
5%- 25% revenue firm	**14.80**	4.06	**16.12**	6.28	4.04	1.87	0.27	8.26	39.95	19.14	100.00
25%- 50% revenue firm	**10.47**	3.89	13.64	**12.28**	6.54	1.66	0.34	8.31	34.07	19.27	100.00
50%- 75% revenue firm	**7.41**	3.47	12.97	8.86	**11.79**	3.68	0.32	7.31	32.55	19.05	100.00
75%- 95% revenue firm	**4.15**	4.20	12.79	8.30	9.54	**7.44**	0.86	6.87	31.01	18.99	100.00
95% revenue firm	**0.80**	2.96	16.75	6.90	6.90	5.91	**4.43**	5.91	31.03	19.21	100.00
Missing: micro firm	**14.28**	4.63	8.50	5.43	4.46	1.52	0.36	**19.58**	33.99	21.52	100.00
A. person not observed	**17.00**	12.29	29.94	18.20	12.43	4.84	0.86	21.44	**0.00**	0.00	100.00
B. person observed, no work	**25.12**	13.50	26.71	16.03	10.29	4.65	1.07	27.75	0.00	**0.00**	100.00
Total	**100.00**	**8.24**	**18.93**	**11.42**	**8.10**	**3.35**	**0.67**	**16.92**	**20.82**	**11.56**	**100.00**

Notes: This table is formed the in following way: for all employment spells before and after prison the firm revenue by spell is taken. The average of those revenues is considered separately for the before and the after prison period, then categorized as shown. Then the distribution of the after prison firm revenues is plotted by the before prison categories

Table 10: Transition in the Firm Capital/Labor Ratio Distribution Before and After Prison

BEFORE \AFTER	**PRE** %	<10% %	10-25% %	25-50% %	50-75% %	75-90% %	90%< %	Missing %	A. %	B. %	Total %
<10% capital / employee	**8.21**	5.72	10.93	4.60	2.94	1.92	1.02	14.31	39.33	19.23	100.00
10-25% capital / employee	**15.33**	9.44	9.59	5.11	4.87	1.64	0.96	10.31	37.43	20.66	100.00
25-50% capital / employee	**11.93**	7.53	8.53	10.28	5.74	2.75	1.12	9.84	34.99	19.21	100.00
50-75% capital / employee	**7.48**	6.66	9.89	6.61	9.99	3.70	1.59	9.89	33.74	17.93	100.00
75-90% capital / employee	**3.29**	4.57	8.30	5.05	6.02	10.11	3.37	10.35	31.29	20.94	100.00
90%<capital / employee	**1.25**	6.31	9.46	5.36	2.52	5.99	8.52	5.36	37.85	18.61	100.00
Missing: micro firm	**14.28**	4.72	20.93	4.90	3.56	1.70	1.01	6.53	35.05	21.60	100.00
A. person not observed	**17.00**	17.34	24.72	14.94	12.94	4.98	1.93	23.14	0.00	0.00	100.00
B. person observed, no work	**25.52**	15.26	32.89	12.63	10.41	4.90	2.36	21.55	0.00	0.00	100.00
Total	**100.00**	**10.47**	**19.79**	**9.20**	**7.67**	**4.37**	**3.67**	**15.09**	**20.82**	**11.56**	**100.00**

Notes: This table is formed the in following way: for all employment spells before and after prison the firm K/L measured in real terms (HUF) by spell is taken. Then the average of those values is considered separately for the before and the after prison period, then categorized as shown. Then the distribution of the after prison firm K/L is plotted by the before prison categories

3 Identification Strategy

The baseline model used to explore post-prison wage penalty for convicts is a flexible panel regression with multiple fixed effects. It builds on the identification strategies used by Jacobson et al. (1993), Cho and Lalonde (2008) and Couch and Placzek (2010), and is specified in the following way:

$$\begin{aligned} \text{Real Wage}_{ijt} =& \alpha + \beta_1 \text{Convict}_i x \text{Before Prison}_{it} + \beta_2 \text{Convict}_i x \text{After Prison}_{it} \\ &+ \text{I'}_{ijt}\gamma + \text{F'}_{jt}\lambda + \text{Fixed Effects} + \epsilon_{ijt} \end{aligned} \tag{1}$$

Index i stands for individual ,t stands for time measured in months and j stands for firm; with *i=1, ... , 4,602,999, t=1, ..., 108, j=1,...,792,944*. In the main models, the dependent variable Real Wage$_{ijt}$ is the real wage a person i earns in a given month t working at a given firm j (adjusted for the number of days worked). The main variables of interests are the first two explanatories. These are dummy variables always taking value 0 for non-convicts and taking value 1 for convicts in month before/after their first observed prison spell. First, the disadvantage of convicts before and after the incarceration compared to the general population is estimated as β_1 and β_2. β_1 and β_2 are expected to be negative reflecting ever-convicted people's disadvantage from the general population based on observed and unobserved traits. Then, the post-prison wage penalty is identified as the absolute difference between β_2 and β_1. The main question of this estimation is whether $\beta_2 > \beta_1$ in absolute terms, that is whether their disadvantage increases after the prison sentence. Such a significant wage penalty means that even the convicts who manage find a job after prison have a worse position on the labour market than they had before. $\mathbf{I}_{ijt}$ includes control variables specific to an individual and the employment history. These variables could be time variant and employment spell-specific, thus are connected to the firms people work at. (For instance tenure on the job is time variant and is related to a person's employment spell at a given firm). $\mathbf{F}_{jt}$ includes firm-specific characteristics, for the workplace of the individuals, which could be time variant. Depending on the specification, different sets of fixed effects are used to capture the unobserved differences, the variance components in the errors. In most specifications errors are clustered by firms to filter common shocks at a firm level.

Whenever a special population of society is analysed, the main difficulty of identification lies in finding a suitable ***control group*** to measure their outcomes against. It is likely that convicts and the general population differ in several observed and unobserved factors. Thus finding a similar enough non-incarcerated control group could always leave some systematic biases. As this makes it difficult to know what exactly β_1 and β_2 captures from all the unknowns, the exact magnitude of these coefficients is not interpreted within this framework. Out of caution, only the absolute difference between β_2 and β_1 which captures the incarceration penalty is analysed. With this interpretation milder assumptions are sufficient regarding the similarity of convicts and non-convicts. It is assumed that those factors which separate convicts and the general population (including the unknowns) have the same effect on the relative wages of the two groups in pre- and post-prison. Therefore, if the disadvantage of convicts is greater after the prison it must be the effect of incarceration (with all other time-varying determinants controlled for). However, this assumption is not a mild one and the measured wage penalty could reflect a mixture of things. It is possible that a prison sentence changes the unobserved characteristics convicts or the marginal effect of those. Some convicts will be pushed further away from legitimate employment in prison: their human capital and social skills could deteriorate, they could lose their non-criminal social ties and build up a criminal social network (Bayer et al., 2009). Others gain education in prison and become more motivated to find and keep legitimate jobs (see Meszaros and Csaki (2011), Pager et al. (2009)). It is impossible to disentangle these individual stories in the data, but it is important to note that the average coefficient could reflect all these effects. Although, the main estimations do not separate these factors the robustness checks of Section 5 aim to elaborate on some of these effects.

Even after finding a way around the problems with the control group there are several other difficulties to face. This study aims to analyse wages but it would be important to know what determines

selection to work, what is the mechanism behind finding employment. Although, building a fully identified two-stage model which describes employment status and wages would worth a separate study this data set is not suitable for it. There is little information on those periods when people do not work as most variables are related to the employment spells. Without modelling the determinants of working and analysing the wages of those who work a positive selection on unobserved characteristics is applied. Employment is not allocated randomly: those are hired who have characteristics rewarded by the labour market. This untreated selection problem does not hurt the identification of wage penalty as long as the process works the same way for convicts before and after incarceration. However, if different groups of the ever convicted population work before and after prison, or some of their characteristics are weighted differently when applying for a job in the two periods, then selection biases our estimates. To understand employment patterns and overcome compositional differences of working convicts, alternative estimates are presented. First, auxiliary estimates were run with the available controls to model employment. Unfortunately, these estimates lack the strength to become proper first stage estimates, but give a rough picture on how employment trends change after prison (Table 11 and 13). Second, the main estimates are rerun with a subsample of convicts who work both before and after prison (Table 18). This robustness check aims to filter compositional difference between working convicts before and after prison, thus mitigates the selection bias.

Another important difficulty in estimating unbiased coefficient is the problem of ***common support***. The main wage regression controls for several characteristics which could affect the labour market outcomes of convicts. However, many of variables categories will apply to only a few of the convicts which makes parameter estimates to be based on rare events and a couple of influential observations. Therefore it helps the stability of estimation if convicts are compared to a subset of non-incarcerated individuals who are more similar to them, even if control variables in the regression take care of this. To achieve this, alternative estimates are presented as robustness checks. First, the main model is re-estimated keeping only low-qualified men in the sample (Section 5.4). Second, a matched non-incarcerated control group is used to re-estimate the model (Section 5.5). The first approach is a rather blunt attempt to homogenize the sample, but it allows within firm comparison of convicts with their colleagues. The second estimation is a proper matching of convicts and the general population based on the first observed years of data. However, as workplaces change, within firm comparison is not possible in the long-run using this sample.

The problem of ***bad controls*** identified by Angrist and Pischke (2008), plagues the estimation strategy of this study along with many wage regressions of labour economics. The bad control problem arises if such variables are used as explanatory variables in a regression which are also outcomes of the treatment studied. In this case incarceration may hurt convicts' wages, but it may also change their place in the occupation hierarchy which drives the wage effect. (Besides occupation other controls could suffer from this issue i.e.: employment contract types). In this sense post-prison occupation is also affected by incarceration and could be analysed as a dependent variable as well. Problem with bad controls is that without fully modelling the relationship between potential earnings, occupational choice and incarceration it is difficult to untangle the causal effects and selection. Modelling this would be a challenge even more detailed available information but it is impossible with the current data. Therefore, the bad control problem is not solved in a fully satisfactory way in this paper. In attempts to handle this the clearest possible way the reduced form estimates of the main models are presented without any potentially bad control (Table 11 and 12. The interpretation of the results possibly plagued with bad controls is with the caveat that some of the results be non-causal and affected by selection. However, interpreting only the difference of coefficients, time-invariant selection effects are not problematic here.

Lastly, there could be ***non-linearities*** in the identified wage penalty both by groups of convicts and in time. Therefore robustness checks are conducted to learn about what effects the average hides. Perhaps most importantly Table 16 analyses separately the wage penalty on the last employment spell before incarceration and the first employment spell after prison. Based on Heckman and Smith

(1999), it is plausible to believe that right before the prison convicts' outcomes are already worse then their average. They could be hurt by the trial or the criminal activity, alternatively bad outcomes could cause criminal activity. It is also a well documented case in the literature that the fist job after prison is the most difficult to secure, thus losses can be especially concentrated there (see Holzer et al. (2006) and Pager et al. (2009)).

4 Results

This section presents the results based on the main estimation strategy in the following order. First, a "raw" set of employment chance and wage penalty regressions are presented. In these estimations only minimal controls and time fixed effects are used. These results shows the baseline penalty of incarceration to be decomposed and the purest difference without potentially bad controls. Second, control variables are introduced to this estimation to see whether they fully explain and eliminate the post-prison penalty. Third, the same exercise is conducted within firm, as ultimately firm decisions lie behind labour market outcomes.

4.1 Raw Difference

Table 11 and 12 show how employment chances and wages change from the before to the after prison period with a minimal set of control variables. Both specifications are OLS estimations with time fixed effects and robust errors. *Employed* as dependent variable takes value 1 if a person works on the 15^{th} of a given month and 0 otherwise. *Ln(Daily RWage* denotes monthly real wages divided by the number of days worked in a given month in natural logarithm. Similarly to other disadvantaged groups of society convicts rarely work and even more rarely work full months. Therefore, wages are adjusted for days worked. *Convict* is a time invariant control which always takes value 1 for ever convicted individuals and 0 for non-convicts. *Convict & Before/After* are interactions of dummies, which always take 0 for non-convicts and take 1 for convicts in months before/after their first observed prison spell. The *length of the first incarceration*, measured in months, is included to proxy the severity of the crime. The *number of prison spells* is used to control for the fact that convicts with short first sentences often have a second prison spell.[10] *Male* and *age* are exogenous controls filtering some basic differences between the two populations. *Year* fixed effects are applied to make use of the panel data and control for changing economic conditions over time.

Overall, these regressions confirm the expected, that convicts are employed far less often and earn lower wages than the general population does. Naturally, a large part of this stems from compositional differences which will be explored in further estimations. For reasons explained before the exact magnitude of the coefficients is not interpreted here, just the difference of post and pre-prison parameters. Those show that the already severe disadvantage in employment chances and wages grows post-prison. There is an additional 6-9% point additional penalty in employment chances and about a 4% larger wage penalty after prison for those who work.

[10] Note that convicts during prison are treated as being out of the labour market. Although, in some cases there is reported wage and firm ID for the incarceration period that is not used. It is not clear whether those reported outcomes are data errors or actual jobs inside/outside the prison. Some penitentiaries provide work programs for inmates and some convicts can stay (at least nominally) involved in family businesses during the detention. Even if data shows real cases of employment, such jobs are of very different nature than working on the open labour market.

Table 11: I. Employment Regression: Raw Difference with Time Fixed Effects

	(1) Employed	(2) Employed	(3) Employed
Convict	-0.324***		
	(0.000228)		
Convict & Before Prison		-0.276***	-0.222***
		(0.000326)	(0.000474)
Convict & After Prison		-0.369***	-0.288***
		(0.000316)	(0.000592)
Prison Spell Length (Month)			-0.000205***
			(0.0000152)
Number of Prison Spells			-0.0528***
			(0.000289)
Fixed Effects	Year	Year	Year
Observations	496,155,726	496,155,726	496,155,726
R^2	0.250	0.250	0.250
Abs. Difference After-Before	-	0.093	0.066
After = Before, F-test 2-sided p	0.000	0.000	0.000
After >Before, F-test 1-sided p	0.000	0.000	0.000

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Full regression results are available in the Appendix: Table 24.

Table 12: I. Wage Regression: Raw Difference with Time Fixed Effects

	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)
Convict	-0.362***		
	(0.000958)		
Convict & Before Prison		-0.308***	-0.253***
		(0.00139)	(0.0022066)
Convict & After Prison		-0.411***	-0.333***
		(0.00132)	(0.00271)
Prison Spell Length (Month)			-0.0005329***
			(.0000671)
Number of Prison Spells			-0.0556***
			(0.001683)
Controls (All Spec.)	Age, Age2, Male (Constant)		
Fixed Effects	Year	Year	Year
Observations	183,159,922	183,159,922	183,159,922
R^2	0.039	0.039	0.039
Abs. Difference After-Before	-	0.103	0.080
After = Before, F-test 2-sided p	0.000	0.000	0.000
After >Before, F-test 1-sided p	0.000	0.000	0.000

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Full regression results are available in the Appendix: Table 25.

4.2 Controlled Difference

Table 13 and 14 show whether the post-prison wage and employment chance penalty change if more factors are controlled for. First, controls on personal health, education and local labour market characteristics are added to both wage and employment regressions. Second, employment spell and firm characteristics are added to the wage regressions, to help a better understanding of earning dynamics. Control variables are added sequentially to identify which of them causes the change in the variables of interest and to keep track of the sample size. All regressions are OLS specifications with year fixed effects. Errors are clustered at the firm level to capture firm specific error structures.

First, controls on personal and family health status are added. It is expected that poorer health, disabilities and caring for family members will hurt employment chances and possibly wages.[11] However, as the descriptives revealed earlier, *health expenditure* is higher for those who are better off, because they have better access to health care. *Care and disability allowances*, which are both time variant dummies indicating allowance receipt in each month, have the expected negative effect on both outcomes.

Second, the level of education is added which proxies ability and skills for each individual who ever worked. It is an approximate variable, which is formed based on the detailed skill and degree requirements of all employment spells of a person.[12] It has 6 levels for those who ever worked: unskilled, some vocational school, vocational school, some tertiary education, tertiary education, entrepreneur (with unreported qualification). Those who never work, thus have unknown education status, serve as a baseline for the employment regressions and unskilled people serve as a baseline for all wage regressions. In all sets of results individual outcomes improve with education.

Third, local labour market characteristics are added based on the reported addresses of the individuals: county-level *unemployment rate* and two dummies showing the *percentage of Roma population* living on the address zip code (baseline: zip codes with 0-5% Roma residents). Yang (2017) and several other studies demonstrated that the tightness of local economies could be decisive in the personal success on the labour market. Higher unemployment rate pushes both employment chances and wages down in the regression. The percentage of minorities living in a given area correlates highly with its prosperity and unemployment rate. However, it has an importance here as disadvantaged and discriminated minorities are over-represented in the prison population. Their labour market outcomes could both be hurt by their criminal past and their racial background (Arnold et al., 2018). Although, the data provides no information on the race of individuals, the percent of roma living on the address zip-code could be a close proxy for it. As expected it has an additional negative effect on both employment and wages.

For the wage regressions *tenure*, *occupation* and *employment contract type* is added to capture employment spell characteristics. Tenure has a positive effect on wages: with longer time spent at the firm wages grow. Occupation is an ISCO-8 compatible variable with 8 categories of jobs: top manager, professional, other manager, other white collar, skilled blue-collar, low-skilled blue collar and unskilled positions. With "top-manager" as a baseline, other categories mostly have the expected sign and are strength. Employment contract types include regular contracts (baseline), public sector work, public work programs (available only in the last year of the data), temporary contracts, entrepreneurs and unclassified categories. Previous tables already suggested that with the dominance of regular contracts this variable will not be the most informative on wage dynamics. While coefficient signs and sizes mostly evolve as expected, some change sign and lose significance across specifications.

[11] Note that none of the allowance receipts prohibit working by law. The Health expenditure variable is measured as the total real state health spending per person per month, in its natural logarithm.

[12] For instance a person is categorized as unskilled if he never had any job with and degree or skill requirement. Some technical school means that the person has only worked in unskilled and low-skilled blue collar positions (such as assembler and machine operator).

Table 13: II. Employment Regression: Controlled Difference with Time Fixed Effects

	(1) Employed	(2) Employed	(3) Employed	(4) Employed
Convict & Before Prison	-0.222***	-0.208***	-0.189***	-0.185***
	(0.000474)	(0.000451)	(0.000414)	(0.000436)
Convict & After Prison	-0.288***	-0.275***	-0.224***	-0.221***
	(0.000592)	(0.000563)	(0.000517)	(0.000549)
Prison Spell Length (Month)	-0.000205***	-0.000241***	-0.000432***	-0.000415***
	(0.0000152)	(0.0000145)	(0.0000133)	(0.0000140)
Number of Prison Spells	-0.0528***	-0.0564***	-0.0205***	-0.0220***
	(0.000289)	(0.000275)	(0.000252)	(0.000270)
Controls (All Spec.)			Age, Age2, Male (Constant)	
Controls ((2) (3) (4))	-	Health Expenditure, Receives Care, Disability Allowance		
Controls ((3) (4))	-	-	Education Level Categories(Approx).	
Controls ((4))	-	-	-	Local Unemp. %, Roma %
Fixed Effects	Year	Year	Year	Year
Observations	496,155,726	496,155,726	496,155,726	487,993,777
R^2	0.250	0.322	0.429	0.431
Abs. Difference After-Before	0.066	0.067	0.035	0.036
After = Before, F-test 2-sided p-val.	0.000	0.000	0.000	0.000
After >Before, F-test 1-sided p-val.	0.000	0.000	0.000	0.000

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Full regression results are available in the Appendix: Table 26.

Table 14: II. Wage Regression: Controlled Difference with Time Fixed Effects

	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Convict & Before Prison	-0.253***	-0.203***	-0.194***	-0.127***	-0.083***	-0.081***
	(0.0119)	(0.0111)	(0.0113)	(0.00950)	(0.00813)	(0.00928)
Convict & After Prison	-0.333***	-0.272***	-0.271***	-0.148***	-0.098***	-0.095***
	(0.0147)	(0.0133)	(0.0139)	(0.0129)	(0.0105)	(0.0109)
Prison Spell Length (Month)	-0.000533	-0.000106	-0.000155	-0.000297	-0.000460*	-0.000463*
	(0.000384)	(0.000312)	(0.000314)	(0.000272)	(0.000245)	(0.000247)
Number of Prison Spells	-0.0556***	-0.0381***	-0.0361***	-0.0372***	-0.0406***	-0.0471***
	(0.00627)	(0.00652)	(0.00688)	(0.00585)	(0.00516)	(0.00671)
Controls (All Spec.)			Age, Age2, Male (Constant)			
Controls ((2)-(6))	-	Health Expenditure, Receives Care or Disability Allowance, Education Level				
Controls ((3)-(6))	-	-	Local Unemloyment Rate %, Roma %			
Controls ((4)-(6))	-	-	-	Occupation, Tenure(Months), Empl. Contract		
Controls ((5)-(6))	-	-	-	-	Firm Size, Industry	
Controls ((6))	-	-	-	-	-	Rev., ValueAdd, K/L
Fixed Effects	Year	Year	Year	Year	Year	Year
Observations	183,159,922	183,159,922	181,069,031	177,408,688	177,408,688	109,034,127
R^2	0.039	0.178	0.184	0.338	0.446	0.433
Abs. Difference After-Before	0.080	0.069	0.077	0.021	0.015	0.014
After = Before, F-test 2-sided p	0.000	0.011	0.009	0.016	0.038	0.041
After >Before, F-test 1-sided p	0.000	0.005	0.005	0.008	0.019	0.021

Clustered standard errors in parentheses: by firm ID.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Full regression results are available in the Appendix: Table 27.

Additionally, firm characteristics are added which could affect the wage dynamics. Their signs and sizes are in line with the literature, suggesting that larger firms (represented as firm *size categories*), those with more *revenue*, higher *capital to labour ratio* and *value added* pay more. There could be severe differences across *industries* (NACE-1 level).[13]

Overall, the controlled models show that the difference between convicts and the general population shrinks with the added explanatory variables, but never disappears. The post-prison wage and employment chance penalty stays significant and sizeable. This means that there is some additional unobserved mechanism which these regressions cannot fully grasp. Note that controls in the employment regression did not change too much on the basic patterns, but this is all the data allowed to control for.

4.3 Within Firm

The first two sets of results have shown that the post-prison penalty on the labour market does not disappear even with a rich set of controls. The labour market seems to treat convicts differently before and after their first observed sentence, but it is not clear yet what mechanism causes it. Ultimately, a within firm investigation might help to identify the reason behind the change. The next set of regressions reveal whether firms' hiring decisions create the difference in the pre- and post-prison outcomes.

Table 15 shows within firm wage regressions using the same set of control variables as before. All specifications are estimated as multi-way fixed effects models controlling for year and firm fixed effects.[14] Errors are clustered at the firm level to capture firm specific error structures.

Table 15: III. Wage Regression: Controlled Difference Within Firm with Time Fixed Effects

	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Convict & Before Prison	-0.110***	-0.102***	-0.062***	-0.052***	-0.062***	-0.062***
	(0.010)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)
Convict & After Prison	-0.139***	-0.123***	-0.052***	-0.045**	-0.022***	-0.022***
	(0.013)	(0.010)	(0.007)	(0.007)	(0.008)	(0.008)
Prison Spell Length (Month)	-0.001**	-0.000	-0.000**	-0.000*	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.050***	-0.027***	-0.034***	-0.033***	-0.039***	-0.039***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Controls (All Spec.)	Age, Age2, Male (Constant)					
Controls ((2)-(6))	-	Health Expenditure, Care/Disability Allowance, Education, Local Unemp. % and Roma %				
Controls ((3)-(6))	-	-	Occupation, Tenure(Months)			
Controls ((4)-(6))	-	-	-	Empl. Contract		
Controls ((5)-(6))	-	-	-	-	Firm Size,Rev., ValueAdd, K/L	
Controls ((5))	-	-	-	-	Industry	-
Fixed Effects	Year	Year	Year	Year	Year	Year
Fixed Effects	Firm	Firm	Firm	Firm	Firm	Firm
Abs. Difference After-Before	0.029	0.021	-0.010*	-0.007*	-0.040*	-0.040*
After = Before, F-test 2-sided p	0.041	0.048	0.122	0.161	0.012	0.012
After >Before, F-test 1-sided p	0.020	0.024	0.061	0.080	0.006	0.006
Observations	183,141,198	181,050,373	177,389,998	177,389,998	109,029,723	109,029,723
R-squared	0.579	0.631	0.695	0.705	0.683	0.683

Clustered standard errors in parentheses: firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Full regression results are available in the Appendix: Table 28.

[13] Note that the number of observations decreases radically once firm characteristics are controlled for. Most of these variables come from balance sheets and the smaller the firms, the less strictly data provision is required

[14] All models are estimated with using the reghdfe package from STATA (Correia, 2016)

The first model captures the within firm wage penalty with minimal controls. As before, this raw penalty reflects compositional differences but it is free from the potential bad control biases. To this model personal characteristics and local labour market controls are added to gain a better understanding. These two models show that there is a within firm wage difference between convicts and the general population and this difference grows after prison. Estimation 4-6 extend the model with employment spell characteristics (including occupation). The last two specifications complete the model with firm level controls. These equations provide interesting conclusions. The within firm wage gap between convicts and the general population decreases and the post-prison wage penalty disappears once employment spell characteristics are added. Moreover, the models even identify a post-prison premium. This means that within firms, within the same kind of employment spells convicts are not worse off after prison. Their relative disadvantage to the general population within firm compared to those working in the same occupation, with the same type of contract, for the same length of time is not growing after prison. Parameter estimates show that occupation seems to play the strongest part in this. This suggests that convicts' overall disadvantage on the labour market comes from that they are hired for worse type of jobs than before prison, but within those jobs they are not treated worse in the firm after prison!

5 Additional Estimations and Robustness Checks

5.1 First Spell After Prison & Last Spell Before Prison - Non-Linear Effects

Ashenfelter and Card (1985), Heckman and Smith (1999) and several other papers document a pre- and post-treatment dip across several program evaluation applications. When analysing the effect of incarceration it is a reasonable assumption that the outcomes of convicts could start deteriorating before the actual prison spell. It is possible that labour market outcomes worsen because of the criminal behaviour, the trial process or both. Alternatively, bad outcomes push some of this population towards crime. In any case, if the last employment spell before prison is already affected by the incarceration in any direct or indirect way, it is worth to treat it separately from other employment spells. It is also very likely that the first employment spell after prison will be the one most harmed by potential adverse effects of incarceration. Holzer et al. (2006), Lundquist et al. (2018) and other studies document that the first job is the most difficult to find and keep. As it can serve as a reference for subsequent job applications, the potential effects of incarceration on the employment spells to follow are mitigated. Due to these reasons it makes sense to treat the first post-prison employment spell separately from others too. To study this potentially non-linearity of the effect of incarceration across employment spells, the main model is re-estimated in the following form:

$$\begin{aligned}\text{Real Wage}_{ijt} =& \alpha + \beta_1 \text{Convict}_i x \text{Before Prison}_{it} + \beta_2 \text{Convict}_i x \text{Last Employment Spell Before Prison}_{it} \\ &+ \beta_3 \text{Convict}_i x \text{First Employment Spell After Prison}_{it} + \beta_4 \text{Convict}_i x \text{After Prison}_{it} \\ &+ \text{I'}_{ijt}\gamma + \text{F'}_{jt}\lambda + \text{Fixed Effects} + \epsilon_{ijt}\end{aligned} \tag{2}$$

This equation introduces two new variables to explore the non-linearities of the pre and post-prison penalty across employment spells. $\text{Convict}_i x$ Last Employment Spell Before Prison_{it} and $\text{Convict}_i x$ First Employment Spell After Prison_{it} are time variant dummy variable interactions. They always take value 0 for non-convicts and take value 1 for convicts in a given month if that month falls within the first/last employment spell after/before prison for a convict. These variables capture the additional disadvantage which is realized right before and after the incarceration on top of the average before/after penalties.[15]

[15]Note that not all convicts have more than one employment spell in the before and after periods.

Table 16: IIb. Wage Regression: Controlled Difference with Time Fixed Effects - First & Last Employment Spell

	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Convict & Before Prison	-0.216***	-0.183***	-0.174***	-0.117***	-0.101***	-0.112***
	(0.0129)	(0.0118)	(0.0119)	(0.00966)	(0.00831)	(0.00971)
Convict & Last Empl. Spell Before Prison	-0.0198*	-0.0511***	-0.0538***	-0.0275**	-0.00544	-0.00212*
	(0.0113)	(0.0162)	(0.0165)	(0.0139)	(0.0121)	(0.0123)
Convict & First Empl. Spell After Prison	-0.0585***	-0.0837***	-0.0895***	-0.114***	-0.0578***	-0.0675***
	(0.0105)	(0.0105)	(0.0107)	(0.0103)	(0.00889)	(0.0104)
Convict & After Prison	-0.212***	-0.245***	-0.241***	-0.0964***	-0.0880***	-0.0908***
	(0.0152)	(0.0137)	(0.0144)	(0.0136)	(0.0113)	(0.0117)
Prison Spell Length (Month)	-0.000495	-0.0000170	-0.0000616	-0.000238	-0.000443*	-0.000416*
	(0.000384)	(0.000315)	(0.000318)	(0.000274)	(0.000246)	(0.000248)
Number of Prison Spells	-0.0543***	-0.0350***	-0.0328***	-0.0354***	-0.0402***	-0.0458***
	(0.00637)	(0.00653)	(0.00690)	(0.00590)	(0.00519)	(0.00676)
Controls (All Spec.)	Age, Age2, Male (Constant)					
Controls ((2)-(6))	-	Health Expenditure, Receives Care or Disability Allowance, Education Level				
Controls ((3)-(6))	-	-	Local Unemloyment Rate %, Roma %			
Controls ((4)-(6))	-	-	-	Occupation, Tenure(Months), Empl. Contract		
Controls ((5)-(6))	-	-	-	-	Firm Size, Industry	
Controls ((6))	-	-	-	-	-	Firm Rev., ValueAdd, K/L
Fixed Effects	Year	Year	Year	Year	Year	Year
Abs. Difference: After-Before	-0.004*	0.062	0.067	-0.0206*	-0.013*	-0.0212*
After = Before, F-test 2-sided p	0.211	0.000	0.000	0.068	0.082	0.060
After >Before, F-test 1-sided p	0.105	0.000	0.000	0.034	0.041	0.029
Abs. Difference: Total After-Total Before	0.0347	0.0946	0.1027	0.0659	0.03936	0.04418
After + First After = Before + Last Before, 2 sided p	0.096	0.000	0.000	0.060	0.090	0.071
After + First After >Before + Last Before, 1-sided p	0.048	0.000	0.000	0.030	0.044	0.036
Observations	183,159,922	183,159,922	181,069,031	177,408,688	177,408,688	109,034,127
R^2	0.039	0.178	0.184	0.338	0.446	0.433

Clustered Standard errors in parentheses: firm ID.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Full regression results can be found in the Appendix, Table 29

Table 17: IIIb. Wage Regression: Controlled Difference Within Firm with Time Fixed Effects, First and Last Employment Spell

VARIABLES	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Convict & Before Prison	-0.115***	-0.110***	-0.056***	-0.048***	-0.055***	-0.055***
	(0.012)	(0.010)	(0.007)	(0.006)	(0.008)	(0.008)
Convict & Last Empl. Spell Before Prison	-0.014*	-0.024**	-0.008*	-0.011*	-0.019**	-0.019**
	(0.010)	(0.011)	(0.005)	(0.006)	(0.009)	(0.009)
Convict & First Empl. Spell After Prison	-0.06*	-0.018**	-0.029***	-0.032***	-0.033***	-0.032***
	(0.004)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Convict & After Prison	-0.140***	-0.127***	-0.009*	-0.005	-0.012	-0.012
	(0.014)	(0.010)	(0.006)	(0.008)	(0.008)	(0.008)
Prison Spell Length (Month)	-0.001**	-0.000	-0.000*	-0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.051***	-0.028***	-0.035***	-0.032***	-0.038***	-0.038***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Controls (All Spec.)	Age, Age2, Male (Constant)					
Controls ((2)-(6))	-	Health Expenditure, Receives Care or Disability Allowance, Education Level				
Controls ((3)-(6))	-	-	Local Unemloyment Rate %, Roma %			
Controls ((4)-(6))	-	-	-	Occupation, Tenure(Months), Empl. Contract		
Controls ((5)-(6))	-	-	-	-	Size, Rev., ValueAdd, K/L	
Controls ((5))	-	-	-	-	Industry	-
Fixed Effects (reghdfe)	Year	Year	Year	Year	Year	Year
Fixed Effects (reghdfe)	Firm	Firm	Firm	Firm	Firm	Firm
Abs. Difference After-Before	0.025	0.017	-0.047*	-0.043*	-0.043*	-0.043*
After = Before, F-test 2-sided p	0.065	0.091	0.122	0.000	0.000	0.000
After >Before, F-test 1-sided p	0.033	0.046	0.061	0.000	0.000	0.000
Abs. Difference Total After- Total Before	0.071	0.011	-0.026*	-0.022*	-0.029*	-0.029*
After + First After = Before + Last Before, 2 sided p	0.000	0.112	0.066	0.062	0.068	0.068
After + First After >Before + Last Before, 1-sided p	0.000	0.055	0.033	0.031	0.034	0.034
Observations	183,141,198	181,050,373	177,389,998	177,389,998	109,029,723	109,029,723
R-squared	0.579	0.631	0.698	0.705	0.683	0.683

Clustered standard errors in parentheses: firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The full results are avaliable in the Apoendic Table 30

Table 16 and 17 both show that the last employment spells before incarceration and the first ones after prison have an additional penalty over the average. The first employment spell after prison especially seems to concentrate the disadvantage. In the controlled OLS specifications, the coefficients on Convict$_i$*x*Before Prison$_{it}$ and Convict$_i$*x*After Prison$_{it}$ do not show a wage penalty for incarceration in some specifications. However, once the employment spells before and after prison are considered the wage-penalty turns into a substantial and significant one. The within firm estimates show a larger disadvantage right before and after prison, but they do not change the overall sign of the penalty.

5.2 Convicts Who Work Both Before and After Prison - Selection Issues

This section explores the importance of selection effects and unobserved changes caused by incarceration which potentially plague the main estimates. The following estimations use the main model on a sub-sample of convicts who work both before and after their incarceration and their colleagues: 6,445 convicts and 1,624,657 never convicted individuals. It is likely that finding a legitimate job is more difficult with a criminal past for the ever-convicted population than it is before the incarceration. Therefore, those convicts who are employed after prison could have better observed and unobserved skills, than averages convicts do. If this is the case, then the pre-prison wage penalty is measured using an average pool of working convicts and the post-prison wage-penalty is measured using a more positively selected group. This way, the pre- and post-prison wage penalty could measure the disadvantage of two different groups. To mitigate such selection effects in measuring the wage penalty the sample of convicts is restricted to those who worked both before and after the sentence in this estimation.[16]

Table 18 presents results from the main model on the restricted sample. Naturally, as the sample selection is based on employment, employment effects are much smaller than before, but the post-prison penalty stays significant. For the wage estimations, both the pre- and post-prison coefficients and the wage-penalty are smaller than they are for the general sample. This could both be explained by the stronger employment records these convicts and by their better observed and unobserved characteristics. However, the importance of this table is showing that it is not selection which drives the conclusions in the main model as those tendencies do not change. Prison sentence draws an employment chance and a wage penalty, which wage penalty only disappears within firm once employment characteristics are controlled for. It is only the magnitude which is different here, smaller than it is before.

Table 18: IV. Wage Regression: Convicts Who Work Before and After Prison and Colleagues

	(1) Raw Employed	(2) Controlled Employed	(3) Raw Ln(Daily RWage)	(4) Controlled Ln(Daily RWage)	(5) Controlled Ln(Daily RWage)	(6) Within Firm, R. Ln(Daily RWage)	(7) Within Firm, C. Ln(Daily RWage)	(8) Within Firm, C. Ln(Daily RWage)
Convict & Before Prison	-0.120***	-0.100***	-0.238***	-0.186***	-0.101***	-0.048***	-0.038***	-0.048***
	(0.002)	(0.002)	(0.025)	(0.023)	(0.021)	(0.017)	(0.013)	(0.016)
Convict & After Prison	-0.190***	-0.172***	-0.331***	-0.192***	-0.102***	-0.063***	-0.010	-0.007
	(0.002)	(0.002)	(0.023)	(0.023)	(0.021)	(0.016)	(0.013)	(0.015)
Prison Spell Length (Month)	0.001***	0.001***	-0.003***	-0.001*	-0.001*	-0.002***	-0.001**	-0.001**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.066***	-0.063***	-0.081***	-0.031**	-0.047***	-0.079***	-0.042***	-0.045***
	(0.001)	(0.001)	(0.013)	(0.013)	(0.014)	(0.010)	(0.009)	(0.011)
Controls (All Spec.)	Age, Age2, Male (Constant)							
Controls ((2)(4)(5)(7)(8))	-	Health Expenditure, Receives Care or Disability Allowance, Education Level,Local Unemloyment Rate %, Roma %						
Controls ((4)(5)(7)(8))	-	-	-	Occupation, Tenure(Months), Empl. Contract				
Controls ((5)(8))	-	-	-	-	Firm Size, Rev., Industry, ValueAdd, K/L			
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year
Fixed Effects	-	-	-	-	-	Firm	Firm	Firm
Cluster	-	-	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID
Observations	176,066,731	173,558,714	103,886,378	100,443,009	58,300,511	103,867,709	100,424,404	58,294,072
R-squared	0.137	0.247	0.050	0.397	0.471	0.501	0.687	0.678
Abs. Diff.: After-Before	.0698	.072	.093	.006	.001	.015	-.028*	-.041*
After = Before F-test 2-sided p	.000	.000	.000	.385	.550	.180	.090	.060
After >Before F-test 1-sided p	.000	.000	.000	.193	.250	.090	.045	.030

Robust and Clustered standard errors in parentheses. Clustering is done by firm ID in the models marked. *** p<0.01, ** p<0.05, * p<0.1
Full regression results are available in the Appendix, Table 31

[16] Note that even for this group it is possible that incarceration has changed their unobserved characteristics or the marginal effect of those on the labour market outcomes.

5.3 Unobserved Recidvism - Post-Prison Baseline

27% of convicts have multiple incarceration spells during the observed period in the data, especially among those who have short first sentences. As explained before, it is possible that some of the sample had a criminal history before the observed time frame. In that case, previous incarcerations already affect their outcomes and the penalty coefficients measure the effect of subsequent prison spells on employment and wages. Based on the criminal literature (see Bhuller et al. (2016), Arnold et al. (2018)), most relapses to crime happens within 3-5 years after release. Convicts who manage to stay out of prison for that long have high chances of escaping recidivism. Cho and Lalonde (2008) and Czafit and Köllő (2015), working with similar data sets, re-estimate their models using a sample of individuals who were out of prison for the first 3 observed years of the data, as this sub-sample is less likely to have criminal history than the overall sample.

Following the same idea, Table 19 shows the result from re-estimating the main model on the sample of individuals who were not in prison during the first 3 years of the observed time-frame. (The restricted sample includes 20,978 convicts and 1,848,988 non-convict colleagues). The employment results show smaller baseline and post-prison disadvantage, but the absolute difference between them is similar to the one measured in the main model. The wage models find only a slight difference in coefficients in favour of this sample, and again, the main conclusions regarding the wage penalty stay the same. These results suggest that some of the sample might had a criminal past and it was reflected in the baseline outcomes, however, this does not substantially change the mechanism how a new prison sentence hurts their outcomes.

Table 19: V. Wage Regression with Those Having No Criminal History

	(1) Raw Employed	(2) Controlled Employed	(3) Raw Ln(Daily RWage)	(4) Controlled Ln(Daily RWage)	(5) Controlled Ln(Daily RWage)	(6) Within Firm, R. Ln(Daily RWage)	(7) Within Firm, C. Ln(Daily RWage)	(8) Within Firm, C. Ln(Daily RWage)
Convict & Before Prison	-0.260***	-0.210***	-0.309***	-0.190***	-0.091***	-0.124***	-0.054***	-0.064***
	(0.001)	(0.001)	(0.014)	(0.012)	(0.011)	(0.011)	(0.006)	(0.008)
Convict & After Prison	-0.321***	-0.272***	-0.410***	-0.201***	-0.093***	-0.144***	-0.018**	-0.018**
	(0.001)	(0.001)	(0.018)	(0.017)	(0.013)	(0.013)	(0.009)	(0.009)
Prison Spell Length (Month)	0.001***	0.001***	-0.000	-0.001	-0.001*	-0.000	-0.000	-0.001**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.049***	-0.044***	-0.056***	-0.040***	-0.044***	-0.048***	-0.036***	-0.040***
	(0.000)	(0.000)	(0.007)	(0.007)	(0.008)	(0.006)	(0.005)	(0.006)
Controls (All Spec.)	Age, Age2, Male (Constant)							
Controls ((2)(4)(5)(7)(8))	-	Health Expenditure, Receives Care or Disability Allowance, Education Level,Local Unemloyment Rate %, Roma %						
Controls ((4)(5)(7)(8))	-	-	-	Occupation, Tenure(Months), Empl. Contract				
Controls ((5)(8))	-	-	-	-	Firm Size, Rev., Industry, ValueAdd, K/L			
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year
Fixed Effects	-	-	-	-	-	Firm	Firm	Firm
Cluster	-	-	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID
Observations	201,631,923	198,709,946	118,483,839	114,509,511	68,761,109	118,464,615	114,490,361	68,754,795
R-squared	0.144	0.249	0.051	0.391	0.475	0.518	0.691	0.685
Abs. Diff.: After-Before	.061	.062	.101	.011	.002	.020	-.036*	-.046*
After = Before F-test 2-sided p	0.000	0.000	0.000	.016	.396	.031	0.000	0.000
After >Before F-test 1-sided p	0.000	0.000	0.000	.081	.198	.016	0.000	0.000

Robust and Clustered standard errors in parentheses. Clustering is done by firm ID in the models marked. *** p<0.01, ** p<0.05, * p<0.1
Full regression results can be found in the Appendix, Table 32

5.4 Low-Skilled Men - Homogenous Sample

Convicts are a very distinct subgroup of the population and some segments of the society are very under-represented in it. For instance, it would be hard to find a highly educated, female professional convict from the IT industry. When a regression controls for these attributes, the few convicts with this combination of characteristics will be influential in estimating the effect of incarceration. As rare observations could move the average effect substantially, restricting the sample to a more homogeneous one helps identifying stable parameters. For this reason the main model is re-estimated using sub-samples which is more similar to convicts.

Table 20: VI. Wage Regression for Men with No Education

	(1) Raw Employed	(2) Controlled Employed	(3) Raw Ln(Daily RWage)	(4) Controlled Ln(Daily RWage)	(5) Controlled Ln(Daily RWage)	(6) Within Firm, R. Ln(Daily RWage)	(7) Within Firm, C. Ln(Daily RWage)	(8) Within Firm, C. Ln(Daily RWage)
Convict & Before Prison	-0.114***	-0.115***	-0.289***	-0.120***	-0.105***	-0.112***	-0.069***	-0.066***
	(0.000)	(0.000)	(0.024)	(0.020)	(0.021)	(0.011)	(0.009)	(0.014)
Convict & After Prison	-0.139***	-0.137***	-0.348***	-0.173**	-0.111**	-0.178***	-0.009*	-0.022**
	(0.001)	(0.000)	(0.027)	(0.033)	(0.030)	(0.013)	(0.014)	(0.015)
Prison Spell Length (Month)	0.000***	0.001***	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.020***	-0.007***	-0.054***	-0.037***	-0.056***	-0.036***	-0.031***	-0.035***
	(0.000)	(0.000)	(0.009)	(0.009)	(0.013)	(0.005)	(0.005)	(0.010)
Controls (All Spec.)	Age, Age2, Male (Constant)							
Controls ((2)(4)(5)(7)(8))	-	Health Expenditure, Receives Care or Disability Allowance, Education Level,Local Unemloyment Rate %, Roma %						
Controls ((4)(5)(7)(8))	-	-	-	Occupation, Tenure(Months), Empl. Contract				
Controls ((5)(8))	-	-	-	-	Firm Size, Rev., Industry, ValueAdd, K/L			
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year
Fixed Effects	-	-	-	-	-	Firm	Firm	Firm
Cluster	-	-	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID
Observations	22,371,085	21,853,346	11,110,575	10,931,942	8,374,116	11,106,785	10,928,213	8,372,018
R-squared	0.159	0.289	0.034	0.251	0.444	0.712	0.744	0.752
Abs. Diff.: After-Before	.025	.022	.059	.053	.006	.066	-.060*	-.044*
After = Before F-test 2-sided p	.024	.029	.008	.007	.165	.004	.004	.012
After >Before F-test 1-sided p	.012	.014	.004	.003	.083	.002	.002	.006

Robust and Clustered standard errors in parentheses. Clustering is done by firm ID in the models marked. *** p<0.01, ** p<0.05, * p<0.1
Full regression results are available in the Appendix 33

Table 20 presents the main model's results using a sub-sample of low-skilled men: 26,762 convicts and 1,322,810 non-convicts.[17] 90% of all convicts are men and 73.4% of them falls into the low-skilled category, so this sample restriction certainly grasp the typical convict. This sample selection might seem blunt at a first glance, but it homogenizes the sample across two crucial determinants of labour market outcomes, yet it leaves enough observations to allow for meaningful within firm comparisons.

Table 20 mostly confirms the expected tendencies. The employment regressions show a smaller disadvantage and prison-penalty than in the main model. This result suggests that the bulk of the disadvantage of convicts in the employment chances can be explained by compositional and educational differences. On the other hand, the wage regression's coefficients and penalty measure have about the same size as in the main specification. This means that the wage disadvantage and the penalty for incarceration persists even when convicts are compared to a more similar population. This could mean that even within the pool of uneducated convicts have such characteristics which hurts their wages. However, a prison sentence still affects their wages and the dynamics is similar to the one in the main model.

5.5 Matched Control Group - Homogenous Sample

Using matched control group is a more elaborate attempt to homogenize the sample of convicts and non-convicts in the analysis. Matched non-incarcerated control groups could help estimating more stable parameters to identify the penalty of prison sentence on the labour market. During the matching I followed the methods of Couch and Placzek (2010), who estimate the earnings losses of displacement using a matched non-displaced control groups and experimented with several alternative specifications. The matching was conducted using the first year of the data, on the sample of those individuals who were not in prison during the first 12 months. Those of this sample who were observed to be incarcerated in later years (convicts) were matched to those who did not spend time in prison during 2003-2011 (non-convicts). This way a group of individuals with similar characteristics are selected, but some become incarcerated later and others don't. The matching assumes that their outcomes would evolve the same way in absence of the incarceration, based on their observed characteristics. Using the matched control groups, the evolution of outcomes and the effect of the prison sentence is evaluated using the remaining years of the data set. [18]

[17] The sample uses men with the variable "qisk" having 0, 1 or 2 value, meaning that they did not work in a single job requiring more skills than a low-skilled blue collar position. They likely to have at most some vocational training.

[18] The longer time frame is used for the matching, the better the quality of the pairings could be. On the other hand, it restricts the time to evaluate the effect of incarceration. Alternative estimations were conducted using the first 2 and 3 years for matching and the rest of the period for evaluation. Those results are not presented here, as their conclusions are very similar to the ones presented here. (These results are available upon request).

The matching between the two groups was implemented based on personal characteristics, local labour market specifics, the amount of time spent at work and the characteristics of employment spells and the firms.[19] Using these variables a propensity score was estimated with a logit model. Based on this propensity score, three types of control samples were selected: (1) an exact nearest neighbour (2) a k-nearest neighbour (k=10) (3) and a kernel matched control sample.[20] Based on the recommended settings of these studies, the matching was conducted using a logit option, the common support observation and a caliper=0.01 for the kernel. The nearest neighbour matches were estimated with no replacement and leaving ties in the control sample as well. The exact matching is the cleanest way is finding each convict a non-convict pair. However, because of the patchy employment histories of convicts and their most-similar counterpart the k-neighbour matching could increase stability. Kernel matching is added for balance, to see how different the results could get when a different technique is used. To check how the matching homogenized the sample, balancing tests were conducted. The tests, which are available in the Appendix Table 34, 35 and 36, show a large difference between convicts and non-convicts on average before the matching and close similarity after the matching.[21]

Table 21: VII. Matched Control Group - 1 Year - Nearest Neighbour 1

VARIABLES	(1) Employed	(2) Employed	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)
Convict & Before Prison	-0.183***	-0.182***	0.044**	-0.002	-0.037**
	(0.002)	(0.001)	(0.021)	(0.016)	(0.016)
Convict & After Prison	-0.194***	-0.197***	-0.126***	-0.060***	-0.055***
	(0.002)	(0.002)	(0.026)	(0.020)	(0.020)
Prison Spell Length (Month)	0.000*	0.000***	-0.001	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Number of Prison Spells	-0.079***	-0.068***	-0.055***	-0.042***	-0.030**
	(0.001)	(0.001)	(0.014)	(0.012)	(0.013)
Controls (All Spec.)	Age, Age2, Male (Constant)				
Controls ((2)(4)(5))	-	Health Exp., Receives Care/ Disab. Allowance, Educ., Local Unemp Rate %, Roma %			
Controls ((4)-(5))	-	-	-	Occupation, Tenure, Empl. Contract	
Controls (((5))	-	-	-	-	Size, Rev., ValueAdd, K/L
Controls ((5))	-	-	-	-	Industry
Observations	1,381,287	1,381,287	737,851	730,289	446,232
R-squared	0.101	0.174	0.025	0.239	0.371
Fixed Effects	Year	Year	Year	Year	Year
Cluster	-	-	Firm	Firm	Firm
Number of Convicts	7012	7012	7012	7012	7012
Number of Non-Convicts	8494	8494	8494	8494	8494
Abs. Diff.: After-Before	.011	.015	.082	.058	.018
After = Before F-test 2-sided p	.021	.020	.000	.000	.018
After >Before F-test 1-sided p	.011	.010	.000	.000	.009

Robust standard errors are used in estimations (1) and (2). Clustered standard errors in estimations (3)-(6): firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The model is estimated on the time-frame 2004-2011. The matching is based on an exact nearest matching on the common support, with no replacement and ties.
Full regression results can be found in the Appendix, Table 37

[19] To be more specific, after trying several set of controls the variables used in the matching based on the best fit were the following: Age, Male, Education, Receives Care/Disability Allowance, Regional Unemployment Rate %, Percent of Months Spent Working, Number of Days Worked in a Month, Monthly Real Wage, Occupation, Firm Size, Industry, Firm Revenue. These variables were used from the collapsed data set describing the first observed years of the sample. (The collapsed dataset includes the mean of Age, Allowance Receipt, Unemployment Rate, Days Worked, Wages, Size and Revenue and the mode of occupation and industry categories. Education is time-variant and the percentage of employed months was used as it is).

[20] The matching was conducted using the psmatch2, nnmatch and teffects packages of STATA, built by Leuven and Sianesi (2018), Becker and Ichino (2002), Abadie et al. (2004).

[21] Note that the nearest neighbour matchings have better balance than the kernel, however, even the kernel estimate is well balanced for the most important variables.

Table 22: VII. Matched Control Group - 1 Year - Nearest Neighbour 10

VARIABLES	(1) Employed	(2) Employed	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)
Convict & Before Prison	-0.166***	-0.167***	-0.015	-0.005	-0.046***
	(0.001)	(0.001)	(0.020)	(0.015)	(0.016)
Convict & After Prison	-0.197***	-0.203***	-0.178***	-0.071***	-0.073***
	(0.002)	(0.002)	(0.025)	(0.019)	(0.020)
Prison Spell Length (Month)	0.000***	0.000***	-0.001	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Number of Prison Spells	-0.075***	-0.065***	-0.055***	-0.040***	-0.026**
	(0.001)	(0.001)	(0.014)	(0.012)	(0.013)
Controls (All Spec.)	Age, Age2, Male (Constant)				
Controls ((2)(4)(5))	-	Health Exp., Receives Care/Disab. Allowance, Educ., Local Unemp %, Roma %			
Controls ((4)-(5))	-	-	-	Occupation, Tenure, Empl. Contract	
Controls (((5))	-	-	-	-	Size, Rev., ValueAdd, K/L
Controls ((5))	-	-	-	-	Industry
Observations	6,743,271	6,743,271	4,047,689	4,007,438	2,749,744
R-squared	0.052	0.143	0.021	0.252	0.401
Fixed Effects	Year	Year	Year	Year	Year
Cluster	-	-	Firm	Firm	Firm
Number of Convicts	7012	7012	7012	7012	7012
Number of Non-Convicts	64348	64348	64348	64348	64348
Abs. Diff.: After-Before	.031	.035	.164	.066	.027
After = Before F-test 2-sided p	.000	.000	.000	.000	.021
After >Before F-test 1-sided p	.000	.000	.000	.000	.010

Robust standard errors are used in estimations (1)(2). Clustered standard errors in estimations (3)-(6): firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The model is estimated on the time-frame 2004-2011. The matching a k-nearest matching (k=10) on the common support, with no replacement and ties.
Full regression results can be found in the Appendix, Table 38

Table 23: VII. Matched Control Group - 1 Year - Kernel

VARIABLES	(1) Employed	(2) Employed	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)
Convict & Before Prison	-0.178***	-0.156***	-0.083***	-0.045***	-0.061***
	(0.001)	(0.001)	(0.021)	(0.016)	(0.016)
Convict & After Prison	-0.201***	-0.182***	-0.138***	-0.109***	-0.109***
	(0.002)	(0.002)	(0.025)	(0.021)	(0.020)
Prison Spell Length (Month)	0.000***	0.000***	-0.001	-0.002**	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Number of Prison Spells	-0.073***	-0.070***	-0.066***	-0.048***	-0.041***
	(0.001)	(0.001)	(0.014)	(0.012)	(0.013)
Controls (All Spec.)	Age, Age2, Male (Constant)				
Controls ((2)(4)(5))	-	Health Exp., Receives Care/ Disab. Allowance, Educ., Local Unemp Rate %, Roma %			
Controls ((4)-(5))	-	-	-	Occupation, Tenure, Empl. Contract	
Controls (((5))	-	-	-	-	Size, Rev., ValueAdd, K/L
Controls ((5))	-	-	-	-	Industry
Observations	179,930,535	179,930,535	129,004,816	128,049,165	79,349,617
R-squared	0.101	0.216	0.014	0.337	0.437
Fixed Effects	Year	Year	Year	Year	Year
Number of Convicts	7012	7012	7012	7012	7012
Number of Non-Convicts	1,868,382	1,868,382	1,868,382	1,868,382	1,868,382
Abs. Diff.: After-Before	.023	.026	.055	0.064	.048
After = Before F-test 2-sided p	.000	.000	.000	.000	.000
After >Before F-test 1-sided p	.000	.000	.000	.000	.000

Robust standard errors are used in estimations (1) and (2). Clustered standard errors in estimations (3)-(6): firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The model is estimated on the time-frame 2004-2011. The matching is based on a kernel matching on the common support, with caliper(0.01).
Full regression results can be found in the Appendix, Table 39

Table 21, 22 and 23 present the main model estimates using a sub-sample of convicts and a matched control group of non-convicts.[22] Similarly to the results presented in the previous section the disadvantage and post-prison penalty in employment chances are smaller compared to the main model, but their main tendencies do not change. The wage regressions shows very different coefficients for the nearest neighbour matchings: no or little disadvantage for convicts before prison with a significant but small difference after prison. These regressions suggest that the matching worked well, pre-prison convicts have similar non-convict counterparts.[23] The emerging wage penalty for the prison sentence show that convicts' outcomes are hurt by the incarceration even if they are compared to the most similar non-convicts. The kernel matching wage regressions coefficients and wage penalty which is found the sample of low-skilled men.[24]

6 Conclusion

In this paper I analysed the effect of a prison sentence on labour market outcomes. I found a substantial wage and employment chance penalty associated with a criminal past across several alternative specifications. Within firm models suggest that the wage-penalty stems from that ex-convicts are hired for worse jobs, shorter employment spells with lower skill requirements than before the incarceration. The downward shift in the occupational hierarchy seems to drive the wage effects. It suggests that unwilling or unable to differentiate similar position employees in wages, firms insure themselves against the risks of hiring ex-convicts by offering them low level jobs with low wages: positions in which chances of damaging the firm are lower. It is likely that ex-convicts accept those offers because they do not have better options. Scarce opportunities could push down their expectations and reservation wages. In some sense this is a labour market inefficiency, a skill-mismatch coming from asymmetric information. Firms hire ex-convicts for worse jobs than they are capable of because they are uncertain about their true qualities. It is likely that low-level jobs and grim career prospects will push even some of those ex-convicts towards crime who tried to make a living on the legitimate labour market. These results suggest that policy efforts to help reintegration should not stop at helping to find a job, but should focus on a wider range of labour market outcomes.

Building on the criminal and displacement literature of labour economics I used a flexible panel specification with multiple fixed effects. I identified the disadvantage of convicts before and after the incarceration compared to the general population and used the absolute difference between those coefficients to identify the penalty of a prison sentence on labour market outcomes. Under the assumption the convicts and the general population have different characteristics which affect their labour market outcomes the same way before and after prison, this identification strategy estimates how labour market penalizes the prison sentence. The conclusions of the main model stay robust across several alternative specifications. The post-prison penalty seems to be concentrated right-after the prison sentence. Some of the sample might have a criminal history at the start of the observed period which already hurts their outcomes. When convicts are compared to their most-similar non-convict counterparts the employment chance penalty improves a bit, but the wage penalty behaves as in the main model.

This paper identified the sources of the post-prison wage penalty, however, there are still several determinants of labour market outcomes which need further investigation. For instance, there is little large scale evidence on how firms evaluate criminal records and how much specific crimes matter for hiring (Pager et al., 2009). It would be also important to know that how job-search mechanisms,

[22] Note that with this simple matching strategy it is not possible to estimate within firm models, as the matched convicts do not necessarily work at the same firms during the evaluation period.

[23] Note that some of the convicts have a short observed period between the time frame of the matching and the prison sentence. This short time window might leave a little time for their outcomes to deviate from the control group's outcomes.

[24] Note that the sample size is very different her from the ones used in the nearest neighbour matchings. It is possible that with a smaller caliper the results would resemble more to the other matching coefficients.

which are used by the general population, work for the group of ex-convicts. Pager et al. (2009), Farber et al. (2016) and Raphael (2010) suggest that references could be crucial in counterbalancing the stigmatizing mark of a criminal record. For instance, former co-workers could recommend ex-convicts to their current workplaces. Such references could increase chances of getting hired and could also mitigate the wage penalty by preventing the downward shifts in the occupational hierarchy. If recommendations are useful in improving the outcomes of ex-convicts, policy tools could use their mechanisms. Raphael (2010), Doleac and Hansen (2016) see transitional employment programs helpful in the reintegration because they provide work-experience and references after release. Overall, more evidence could help to understand other important mechanisms which shape the labour market outcomes of ex-convicts, to achieve better reintegration policies based on their results.

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Appendix

Table 24: I. Employment Regression: Raw Difference with Time Fixed Effects

	(1) Employed	(2) Employed	(3) Employed
Convict	-0.324***		
	(0.000228)		
Convict & Before Prison		-0.276***	-0.222***
		(0.000326)	(0.000474)
Convict & After Prison		-0.369***	-0.288***
		(0.000316)	(0.000592)
Prison Spell Length (Month)			-0.000205***
			(0.0000152)
Number of Prison Spells			-0.0528***
			(0.000289)
Age	0.0553***	0.0553***	0.0553***
	(0.00000463)	(0.00000463)	(0.00000463)
Age Squared	-0.000673***	-0.000674***	-0.000674***
	(5.33e-08)	(5.33e-08)	(5.33e-08)
Male	0.0348***	0.0348***	0.0348***
	(0.0000379)	(0.0000379)	(0.0000379)
Constant	-0.544***	-0.545***	-0.544***
	(0.000104)	(0.000104)	(0.000104)
Fixed Effects	Year	Year	Year
Observations	496155726	496155726	496155726
R^2	0.250	0.250	0.250
Abs. Difference After-Before	-	0.093	0.066
After = Before, F-test 2-sided p-val	0.000	0.000	0.000
After >Before, F-test 1-sided p-val.	0.000	0.000	0.000

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25: I. Wage Regression: Raw Difference with Time Fixed Effects

	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)
Convict	-0.362***		
	(0.000958)		
Convict & Before Prison		-0.308***	-0.253***
		(0.00139)	(0.0022066)
Convict & After Prison		-0.411***	-0.333***
		(0.00132)	(0.00271)
Prison Spell Length (Month)			-0.0005329***
			(.0000671)
Number of Prison Spells			-0.0556***
			(0.001683)
Age	0.0797***	0.0798***	0.0798***
	(0.0000347)	(0.0000347)	(0.0000347)
Age Squared	-0.000901***	-0.000902***	-0.000902***
	(0.000000426)	(0.000000426)	(0.000000426)
Male	0.0736***	0.0737***	0.0737***
	(0.000110)	(0.000110)	(0.000110)
Constant	6.714***	6.713***	6.713***
	(0.000699)	(0.000699)	(0.000699)
Fixed Effects	Year	Year	Year
Observations	183,159,922	183,159,922	183,159,922
R^2	0.039	0.039	0.039
Abs. Difference After-Before	-	0.103	0.08
After = Before, F-test 2-sided p	0.000	0.000	0.000
After >Before, F-test 1-sided p	0.000	0.000	0.000

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: II. Employment Regression: Controlled Difference with Time Fixed Effects

	(1) Employed	(2) Employed	(3) Employed	(4) Employed
Convict & Before Prison	-0.222***	-0.208***	-0.189***	-0.185***
	(0.000474)	(0.000451)	(0.000414)	(0.000436)
Convict & After Prison	-0.288***	-0.275***	-0.224***	-0.221***
	(0.000592)	(0.000563)	(0.000517)	(0.000549)
Prison Spell Length (Month)	-0.000205***	-0.000241***	-0.000432***	-0.000415***
	(0.0000152)	(0.0000145)	(0.0000133)	(0.0000140)
Number of Prison Spells	-0.0528***	-0.0564***	-0.0205***	-0.0220***
	(0.000289)	(0.000275)	(0.000252)	(0.000270)
Age	0.0553***	0.0585***	0.0315***	0.0319***
	(0.00000463)	(0.00000443)	(0.00000501)	(0.00000507)
Age Squared	-0.000674***	-0.000706***	-0.000362***	-0.000367***
	(5.33e-08)	(5.11e-08)	(5.99e-08)	(6.06e-08)
Male	0.0348***	0.0337***	0.0159***	0.0162***
	(0.0000379)	(0.0000372)	(0.0000350)	(0.0000352)
Ln(Real Health Expenditure)		0.0144***	0.00856***	0.00823***
		(0.00000456)	(0.00000423)	(0.00000429)
Receives Care Allowance		-0.432***	-0.401***	-0.402***
		(0.0000966)	(0.0000887)	(0.0000892)
Receives Disability Pension		-0.365***	-0.216***	-0.216***
		(0.0000678)	(0.0000642)	(0.0000646)
Education: none			0.218***	0.219***
(always unskilled)			(0.0000854)	(0.0000865)
Education: some technical			0.446***	0.443***
(max. low-skilled blue)			(0.0000963)	(0.0000973)
Education: technical school			0.415***	0.413***
(max. skilled blue)			(0.0000607)	(0.0000614)
Education: some tertiary			0.487***	0.482***
(max. white/professional)			(0.0000585)	(0.0000593)
Education: tertiary			0.552***	0.547***
(max. manager top/other)			(0.0000856)	(0.0000864)
Education: unknown			0.358***	0.355***
(entrepreneur)			(0.0000537)	(0.0000544)
Regional Unemp Rate %				-0.171***
				(0.000703)
Roma 5-10% zipcode				-0.0139***
				(0.0000575)
Roma 10%+ zipcode				-0.0244***
				(0.0001000)
Constant	-0.544***	-0.691***	-0.501***	-0.489***
	(0.000104)	(0.000107)	(0.000100)	(0.000108)
Fixed Effects	Year	Year	Year	Year
Observations	496,155,726	496,155,726	496,155,726	487,993,777
R^2	0.250	0.322	0.429	0.431
Abs. Difference After-Before	0.066	0.067	0.035	0.036
After = Before, F-test 2-sided p-val.	0.000	0.000	0.000	0.000
After >Before, F-test 1-sided p-val.	0.000	0.000	0.000	0.000

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 27: II. Wage Regression: Controlled Difference with Time Fixed Effects

	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Convict & Before Prison	-0.253***	-0.203***	-0.194***	-0.127***	-0.083***	-0.081***
	(0.0119)	(0.0111)	(0.0113)	(0.00950)	(0.00813)	(0.00928)
Convict & After Prison	-0.333***	-0.272***	-0.271***	-0.148***	-0.098***	-0.095***
	(0.0147)	(0.0133)	(0.0139)	(0.0129)	(0.0105)	(0.0109)
Prison Spell Length (Month)	-0.000533	-0.000106	-0.000155	-0.000297	-0.000460*	-0.000463*
	(0.000384)	(0.000312)	(0.000314)	(0.000272)	(0.000245)	(0.000247)
Number of Prison Spells	-0.0556***	-0.0381***	-0.0361***	-0.0372***	-0.0406***	-0.0471***
	(0.00627)	(0.00652)	(0.00688)	(0.00585)	(0.00516)	(0.00671)
Age	0.0798***	0.0662***	0.0676***	0.0347***	0.0331***	0.0356***
	(0.00203)	(0.00173)	(0.00172)	(0.00101)	(0.000790)	(0.000658)
Age Squared	-0.000902***	-0.000721***	-0.000738***	-0.000389***	-0.000370***	-0.000418***
	(0.0000247)	(0.0000216)	(0.0000212)	(0.0000129)	(0.0000110)	(0.00000844)
Male	0.0737***	0.173***	0.174***	0.214***	0.209***	0.233***
	(0.0129)	(0.0108)	(0.0108)	(0.00715)	(0.00657)	(0.00603)
Ln(Real Health Expenditure)		0.00312***	0.00320***	-0.000427	-0.00443***	-0.00476***
		(0.000342)	(0.000336)	(0.000297)	(0.000231)	(0.000256)
Receives Care Allowance		-0.569***	-0.571***	-0.515***	-0.476***	-0.443***
		(0.00827)	(0.00815)	(0.00646)	(0.00777)	(0.0102)
Receives Disability Pension		-0.591***	-0.579***	-0.463***	-0.466***	-0.455***
		(0.00745)	(0.00727)	(0.00682)	(0.0128)	(0.0176)
Education: some technical (max. low-skilled blue)		0.354*** (0.0209)	0.346*** (0.0207)	0.0700*** (0.0113)	0.0695*** (0.0106)	0.0939*** (0.0112)
Education: technical school (max. skilled blue)		0.210*** (0.0132)	0.202*** (0.0133)	0.0564*** (0.00588)	0.0418*** (0.00658)	0.0641*** (0.00599)
Education: some tertiary (max. white/professional)		0.706*** (0.0126)	0.687*** (0.0123)	0.0891*** (0.00830)	0.0869*** (0.0102)	0.116*** (0.0133)
Education: tertiary (max. manager top/other)		0.743*** (0.0166)	0.722*** (0.0165)	0.148*** (0.00792)	0.166*** (0.00680)	0.192*** (0.00690)
Education: unknown (entrepreneur)		0.142*** (0.0141)	0.132*** (0.0140)	-0.0124* (0.00697)	0.0599*** (0.00657)	0.0616*** (0.00634)
Regional Unemp Rate %			-1.781***	-1.563***	-1.834***	-2.043***
			(0.235)	(0.164)	(0.151)	(0.117)
Roma 5-10% zipcode			-0.0572***	-0.0339***	-0.0444***	-0.0484***
			(0.00746)	(0.00688)	(0.00575)	(0.00548)
Roma 10%+ zipcode			-0.0631***	-0.0408***	-0.0550***	-0.0649***
			(0.0140)	(0.00745)	(0.00733)	(0.00823)
Tenure on Job (Month)				0.00412***	0.00331***	0.00321***
				(0.000184)	(0.000139)	(0.000104)
Occupation: Other manager				-0.0572***	-0.0327**	-0.00638
				(0.0156)	(0.0129)	(0.0112)
Occupation: Professional				0.148***	0.0420	0.197***
				(0.0322)	(0.0266)	(0.0151)
Occupation: White Collar				-0.232***	-0.330***	-0.241***
				(0.0207)	(0.0160)	(0.0103)
Occupation: Skilled Blue Collar				-0.596***	-0.632***	-0.562***
				(0.0210)	(0.0158)	(0.00847)
Occupation: Low-Skilled Blue				-0.441***	-0.626***	-0.556***
				(0.0231)	(0.0190)	(0.0142)
Occupation: Unskilled				-0.752***	-0.837***	-0.763***
				(0.0222)	(0.0196)	(0.00856)
Occupation: Unknown:entrepreneur				-0.0855***	-0.0842***	-0.0855***
				(0.0155)	(0.0161)	(0.0153)

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	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Employment Type: Public Sector				-0.174***	-0.0927***	-0.445***
				(0.0222)	(0.0216)	(0.0502)
Employment Type: Public Work Program				-0.879***	-0.504***	-0.316***
				(0.0263)	(0.0195)	(0.00755)
Employment Type: Temp. Contract				-0.134***	-0.0851***	-0.783***
				(0.0272)	(0.0289)	(0.0987)
Employment Type: Entrepreneur				-0.161***	0.0873***	0.106***
				(0.0262)	(0.0208)	(0.0161)
Employment Type: Other				-0.956***	-0.806***	-0.451***
				(0.0373)	(0.0297)	(0.0269)
Firm Size: 10-50					0.273***	0.273***
					(0.00286)	(0.00302)
Firm Size: 50-250					0.507***	0.502***
					(0.00604)	(0.00663)
Firm Size: 250+					0.647***	0.652***
					(0.0139)	(0.0153)
Firm Revenue (Real, HUF)						0.000000119**
						(5.38e-08)
Firm Value Added (Real, HUF)						5.56e-10**
						(2.29e-10)
Firm K/L ratio						0.000000286***
						(8.84e-08)
Firm Industry: Mining					0.309***	0.318***
					(0.0429)	(0.0417)
Firm Industry: Manufacturing					0.0770***	0.0746***
					(0.0129)	(0.0115)
Firm Industry: Electricity, water, waste					0.233***	0.225***
					(0.0326)	(0.0305)
Firm Industry: Construction					-0.0133	-0.00920
					(0.0120)	(0.0116)
Firm Industry: Trade					-0.0000357	-0.00240
					(0.0134)	(0.0149)
Firm Industry: Hotel					-0.115***	-0.105***
					(0.0149)	(0.0152)
Firm Industry: Transport, post					0.0616	0.0288
					(0.0479)	(0.0502)
Firm Industry: Finance					0.401***	0.348***
					(0.0434)	(0.0463)
Firm Industry: Real estate					-0.0141	-0.00714
					(0.0124)	(0.0126)
Firm Industry: IT, RD					0.207***	0.180***
					(0.0238)	(0.0230)
Firm Industry: Public					-0.0113	-0.0182
					(0.0139)	(0.0140)
Firm Industry: Other					-0.00429	0.00388
					(0.0130)	(0.0130)
Firm Industry: small enterprise					-0.106***	-0.0314*
					(0.0105)	(0.0161)
Constant	6.713***	6.479***	6.576***	7.984***	7.713***	7.556***
	(0.0451)	(0.0408)	(0.0431)	(0.0362)	(0.0299)	(0.0205)
Fixed Effects	Year	Year	Year	Year	Year	Year
Observations	183159922	183159922	181069031	177408688	177408688	109034127
R^2	0.039	0.178	0.184	0.338	0.446	0.433
Abs. Difference After-Before	0.080	0.069	0.077	0.021	0.015	0.014
After = Before, F-test 2-sided p	0.000	0.011	0.009	0.016	0.038	0.041
After >Before, F-test 1-sided p	0.000	0.005	0.005	0.008	0.019	0.021

Clustered standard errors in parentheses: by firm ID.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Baselines for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode
Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture

Table 28: III. Wage Regression: Controlled Difference Within Firm with Time Fixed Effects

	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Convict & Before Prison	-0.110***	-0.102***	-0.062***	-0.052***	-0.062***	-0.062***
	(0.010)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)
Convict & After Prison	-0.139***	-0.123***	-0.052***	-0.045**	-0.022***	-0.022***
	(0.013)	(0.010)	(0.007)	(0.007)	(0.008)	(0.008)
Prison Spell Length (Month)	-0.001**	-0.000	-0.000**	-0.000*	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.050***	-0.027***	-0.034***	-0.033***	-0.039***	-0.039***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Age	0.069***	0.064***	0.036***	0.030***	0.034***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Age Squared	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.146***	0.160***	0.146***	0.151***	0.174***	0.174***
	(0.009)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
Ln(Real Health Expenditure)		-0.006***	-0.008***	-0.008***	-0.008***	-0.008***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Receives Care Allowance		-0.460***	-0.458***	-0.428***	-0.406***	-0.406***
		(0.009)	(0.008)	(0.007)	(0.008)	(0.008)
Receives Disability Pension		-0.376***	-0.337***	-0.311***	-0.285***	-0.285***
		(0.008)	(0.006)	(0.006)	(0.008)	(0.008)
Education: some technical (max. low-skilled blue)		0.240***	0.068***	0.077***	0.081***	0.081***
		(0.016)	(0.008)	(0.007)	(0.008)	(0.008)
Education: technical school (max. skilled blue)		0.266***	0.042***	0.060***	0.063***	0.063***
		(0.008)	(0.005)	(0.004)	(0.004)	(0.004)
Education: some tertiary (max. white/professional)		0.505***	0.074***	0.091***	0.095***	0.095***
		(0.016)	(0.005)	(0.004)	(0.004)	(0.004)
Education: tertiary (max. manager top/other)		0.791***	0.197***	0.207***	0.222***	0.222***
		(0.015)	(0.007)	(0.005)	(0.005)	(0.005)
Education: unknown (entrepreneur)		0.364***	0.056***	0.097***	0.090***	0.090***
		(0.014)	(0.005)	(0.004)	(0.004)	(0.004)
Regional Unemp Rate %		-1.057***	-0.908***	-0.945***	-1.143***	-1.143***
		(0.082)	(0.073)	(0.072)	(0.078)	(0.078)
Roma 5-10% zipcode		-0.060***	-0.029***	-0.020***	-0.026***	-0.026***
		(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
Roma 10%+ zipcode		-0.085***	-0.042***	-0.029***	-0.036***	-0.036***
		(0.009)	(0.005)	(0.006)	(0.007)	(0.007)
Tenure on Job (Month)			0.002***	0.002***	0.003***	0.003***
			(0.000)	(0.000)	(0.000)	(0.000)
Occupation: Other manager			-0.067***	-0.103***	-0.060***	-0.060***
			(0.014)	(0.012)	(0.010)	(0.010)
Occupation: Professional			-0.077***	-0.143***	-0.067***	-0.067***
			(0.018)	(0.018)	(0.014)	(0.014)
Occupation: White Collar			-0.430***	-0.492***	-0.385***	-0.385***
			(0.016)	(0.015)	(0.009)	(0.009)
Occupation: Skilled Blue Collar			-0.582***	-0.651***	-0.569***	-0.569***
			(0.016)	(0.016)	(0.009)	(0.009)
Occupation: Low-Skilled Blue			-0.659***	-0.714***	-0.636***	-0.636***
			(0.018)	(0.018)	(0.014)	(0.014)
Occupation: Unskilled			-0.822***	-0.840***	-0.738***	-0.738***
			(0.023)	(0.017)	(0.008)	(0.008)
Occupation: Unknown:entrepreneur			-0.189***	-0.061***	-0.206***	-0.206***
			(0.022)	(0.022)	(0.024)	(0.024)
Employment Type: Public Sector				-0.224***	-0.462***	-0.462***
				(0.020)	(0.046)	(0.046)
Employment Type: Public Work Program				-0.345***	-0.175***	-0.175***
				(0.019)	(0.008)	(0.008)
Employment Type: Temp. Contract				0.033	0.152***	0.152***
				(0.021)	(0.016)	(0.016)
Employment Type: Entrepreneur				0.032	-0.141***	-0.141***
				(0.020)	(0.039)	(0.039)
Employment Type: Other				-0.947***	-0.638***	-0.638***
				(0.032)	(0.036)	(0.036)

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	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Firm Size: 10-50					0.045***	0.045***
					(0.001)	(0.001)
Firm Size: 50-250					0.068***	0.068***
					(0.003)	(0.003)
Firm Size: 250+					0.064***	0.064***
					(0.006)	(0.006)
Firm Revenue (Real, HUF)					0.000**	0.000**
					(0.000)	(0.000)
Firm Value Added (Real, HUF)					0.000***	0.000***
					(0.000)	(0.000)
Firm K/L ratio					0.000**	0.000***
					(0.000)	(0.000)
Firm Industry: Mining					0.094***	
					(0.036)	
Firm Industry: Manufacturing					0.027***	
					(0.010)	
Firm Industry: Electricity, water, waste					0.047**	
					(0.021)	
Firm Industry: Construction					0.041***	
					(0.011)	
Firm Industry: Trade					0.025**	
					(0.010)	
Firm Industry: Hotel					0.032***	
					(0.012)	
Firm Industry: Transport, post					0.024	
					(0.017)	
Firm Industry: Finance					0.047**	
					(0.021)	
Firm Industry: Real estate					0.037***	
					(0.011)	
Firm Industry: IT, RD					0.007	
					(0.015)	
Firm Industry: Public: govt, health, educ					0.022*	
					(0.013)	
Firm Industry: Other					0.026**	
					(0.011)	
Fixed Effects	Year	Year	Year	Year	Year	Year
Fixed Effects	Firm	Firm	Firm	Firm	Firm	Firm
Abs. Difference After-Before	0.029	0.021	-0.010*	-0.007*	-0.040*	-0.040*
After = Before, F-test 2-sided p	0.041	0.048	0.122	0.161	0.012	0.012
After >Before, F-test 1-sided p	0.020	0.024	0.061	0.080	0.006	0.006
Observations	183,141,198	181,050,373	177,389,998	177,389,998	109,029,723	109,029,723
R-squared	0.579	0.631	0.695	0.705	0.683	0.683

Clustered standard errors in parentheses: firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Baseline for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode
Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture

Table 29: IIb. Wage Regression: Controlled Difference with Time Fixed Effects, First & Last Employment Spell

	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Convict & Before Prison	-0.216***	-0.183***	-0.174***	-0.117***	-0.101***	-0.112***
	(0.0129)	(0.0118)	(0.0119)	(0.00966)	(0.00831)	(0.00971)
Convict & Last Empl. Spell Before Prison	-0.0198*	-0.0511***	-0.0538***	-0.0275**	-0.00544	-0.00212*
	(0.0113)	(0.0162)	(0.0165)	(0.0139)	(0.0121)	(0.0123)
Convict & First Empl. Spell After Prison	-0.0585***	-0.0837***	-0.0895***	-0.114***	-0.0578***	-0.0675***
	(0.0105)	(0.0105)	(0.0107)	(0.0103)	(0.00889)	(0.0104)
Convict & After Prison	-0.212***	-0.245***	-0.241***	-0.0964***	-0.0880***	-0.0908***
	(0.0152)	(0.0137)	(0.0144)	(0.0136)	(0.0113)	(0.0117)
Prison Spell Length (Month)	-0.000495	-0.0000170	-0.0000616	-0.000238	-0.000443*	-0.000416*
	(0.000384)	(0.000315)	(0.000318)	(0.000274)	(0.000246)	(0.000248)
Number of Prison Spells	-0.0543***	-0.0350***	-0.0328***	-0.0354***	-0.0402***	-0.0458***
	(0.00637)	(0.00653)	(0.00690)	(0.00590)	(0.00519)	(0.00676)
Age	0.0798***	0.0662***	0.0676***	0.0347***	0.0331***	0.0356***
	(0.00203)	(0.00173)	(0.00172)	(0.00101)	(0.000790)	(0.000658)
Age Squared	-0.000902***	-0.000721***	-0.000738***	-0.000389***	-0.000370***	-0.000418***
	(0.0000247)	(0.0000216)	(0.0000212)	(0.0000129)	(0.0000110)	(0.00000844)
Male	0.0737***	0.173***	0.174***	0.214***	0.209***	0.233***
	(0.0129)	(0.0108)	(0.0108)	(0.00715)	(0.00658)	(0.00603)
Ln(Real Health Expenditure)		0.00312***	0.00320***	-0.000427	-0.00443***	-0.00476***
		(0.000342)	(0.000336)	(0.000297)	(0.000231)	(0.000256)
Receives Care Allowance		-0.569***	-0.571***	-0.515***	-0.476***	-0.443***
		(0.00827)	(0.00815)	(0.00646)	(0.00777)	(0.0102)
Receives Disability Pension		-0.591***	-0.579***	-0.462***	-0.466***	-0.455***
		(0.00745)	(0.00727)	(0.00682)	(0.0128)	(0.0176)
Education: some technical (max. low-skilled blue)		0.354***	0.346***	0.0700***	0.0694***	0.0939***
		(0.0209)	(0.0207)	(0.0113)	(0.0106)	(0.0112)
Education: technical school (max. skilled blue)		0.210***	0.202***	0.0563***	0.0418***	0.0640***
		(0.0132)	(0.0133)	(0.00588)	(0.00658)	(0.00599)
Education: some tertiary (max. white/professional)		0.706***	0.687***	0.0889***	0.0869***	0.116***
		(0.0126)	(0.0123)	(0.00830)	(0.0102)	(0.0133)
Education: tertiary (max. manager top/other)		0.743***	0.722***	0.148***	0.166***	0.192***
		(0.0166)	(0.0165)	(0.00792)	(0.00680)	(0.00690)
Education: unknown (entrepreneur)		0.142***	0.132***	-0.0126*	0.0599***	0.0615***
		(0.0141)	(0.0140)	(0.00697)	(0.00657)	(0.00634)
Regional Unemp Rate %			-1.781***	-1.563***	-1.834***	-2.043***
			(0.235)	(0.164)	(0.151)	(0.117)
Roma 5-10% zipcode			-0.0572***	-0.0339***	-0.0444***	-0.0484***
			(0.00746)	(0.00688)	(0.00575)	(0.00548)
Roma 10%+ zipcode			-0.0631***	-0.0408***	-0.0550***	-0.0649***
			(0.0140)	(0.00745)	(0.00734)	(0.00823)
Tenure on Job (Month)				0.00412***	0.00331***	0.00321***
				(0.000184)	(0.000139)	(0.000105)
Occupation: Other manager				0.0572***	-0.0327**	0.00638
				(0.0156)	(0.0129)	(0.0112)
Occupation: Professional				0.148***	0.0420	0.197***
				(0.0322)	(0.0266)	(0.0151)
Occupation: White Collar				-0.232***	-0.330***	-0.241***
				(0.0207)	(0.0160)	(0.0103)
Occupation: Skilled Blue Collar				-0.596***	-0.632***	-0.562***
				(0.0210)	(0.0158)	(0.00847)
Occupation: Low-Skilled Blue				-0.441***	-0.626***	-0.556***
				(0.0231)	(0.0190)	(0.0142)
Occupation: Unskilled				-0.752***	-0.837***	-0.763***
				(0.0222)	(0.0196)	(0.00856)
Occupation: Unknown:entrepreneur				-0.0855***	-0.0842***	-0.0855***
				(0.0155)	(0.0161)	(0.0153)

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	(1) Ln(Daily RWage)	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Employment Type: Public Sector				-0.174***	-0.0927***	-0.445***
				(0.0222)	(0.0216)	(0.0502)
Employment Type: Public Work Program				-0.879***	-0.504***	-0.316***
				(0.0263)	(0.0195)	(0.00755)
Employment Type: Temp. Contract				-0.134***	-0.0849***	-0.783***
				(0.0271)	(0.0289)	(0.0987)
Employment Type: Entrepreneur				-0.161***	0.0872***	0.106***
				(0.0262)	(0.0208)	(0.0161)
Employment Type: Other				-0.956***	-0.806***	-0.451***
				(0.0373)	(0.0297)	(0.0269)
Firm Size: 10-50					0.273***	0.273***
					(0.00286)	(0.00302)
Firm Size: 50-250					0.507***	0.502***
					(0.00604)	(0.00663)
Firm Size: 250+					0.647***	0.652***
					(0.0139)	(0.0153)
Firm Revenue (Real, HUF)						0.000000119**
						(5.38e-08)
Firm Value Added (Real, HUF)						5.56e-10**
						(2.29e-10)
Firm K/L ratio						0.000000286***
						(8.84e-08)
Firm Industry: Mining					0.309***	0.318***
					(0.0429)	(0.0417)
Firm Industry: Manufacturing					0.0770***	0.0746***
					(0.0129)	(0.0115)
Firm Industry: Electricity, water, waste					0.233***	0.225***
					(0.0326)	(0.0305)
Firm Industry: Construction					-0.0133	-0.00920
					(0.0120)	(0.0116)
Firm Industry: Trade					-0.0000428	-0.00240
					(0.0134)	(0.0149)
Firm Industry: Hotel					-0.115***	-0.105***
					(0.0149)	(0.0152)
Firm Industry: Transport, post					0.0616	0.0288
					(0.0479)	(0.0502)
Firm Industry: Finance					0.401***	0.348***
					(0.0434)	(0.0463)
Firm Industry: Real estate					-0.0141	-0.00714
					(0.0124)	(0.0126)
Firm Industry: IT, RD					0.207***	0.180***
					(0.0238)	(0.0230)
Firm Industry: Public: govt, health, educ					-0.0113	-0.0182
					(0.0139)	(0.0140)
Firm Industry: Other					-0.00430	0.00387
					(0.0130)	(0.0130)
Firm Industry: small enterprise					-0.106***	-0.0314*
					(0.0105)	(0.0161)
Constant	6.713***	6.479***	6.576***	7.984***	7.714***	7.556***
	(0.0451)	(0.0408)	(0.0431)	(0.0362)	(0.0299)	(0.0205)
Fixed Effects	Year	Year	Year	Year	Year	Year
After = Before, F-test 2-sided p	0.211	0.000	0.000	0.068	0.082	0.060
After >Before, F-test 1-sided p	0.105	0.000	0.000	0.034	0.041	0.029
Abs. Difference: Total After-Total Before	0.0347	0.0946	0.1027	0.0659	0.03936	0.04418
After + First After = Before + Last Before, 2 sided p	0.096	0.000	0.000	0.060	0.090	0.071
After + First After >Before + Last Before, 1-sided p	0.048	0.000	0.000	0.030	0.044	0.036
Observations	183,159,922	183,159,922	181,069,031	177,408,688	177,408,688	109,034,127
R^2	0.039	0.178	0.184	0.338	0.446	0.433

Clustered Standard errors in parentheses: firm ID.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Baselines for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode

Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture

Table 30: IIIb. Wage Regression: Controlled Difference Within Firm with Time Fixed Effects, First and Last Employment Spell

VARIABLES	(1) lwage_rmd	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Convict & Before Prison	-0.115***	-0.110***	-0.056***	-0.048***	-0.055***	-0.055***
	(0.012)	(0.010)	(0.007)	(0.006)	(0.008)	(0.008)
Convict & Last Empl. Spell Before Prison	-0.014*	-0.024**	-0.008*	-0.011*	-0.019**	-0.019**
	(0.010)	(0.011)	(0.005)	(0.006)	(0.009)	(0.009)
Convict & First Empl. Spell After Prison	-0.06*	-0.018**	-0.029***	-0.032***	-0.033***	-0.032***
Spell After Prison	(0.004)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Convict & After Prison	-0.140***	-0.127***	-0.009*	-0.005	-0.012	-0.012
	(0.014)	(0.010)	(0.006)	(0.008)	(0.008)	(0.008)
Prison Spell Length (Month)	-0.001**	-0.000	-0.000*	-0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.051***	-0.028***	-0.035***	-0.032***	-0.038***	-0.038***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Age	0.069***	0.064***	0.031***	0.030***	0.034***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Age Squared	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.146***	0.160***	0.143***	0.151***	0.174***	0.174***
	(0.009)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
Ln(Real Health Expenditure)		-0.006***	-0.008***	-0.008***	-0.008***	-0.008***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Receives Care Allowance		-0.460***	-0.423***	-0.428***	-0.406***	-0.406***
		(0.009)	(0.008)	(0.007)	(0.008)	(0.008)
Receives Disability Pension		-0.376***	-0.308***	-0.311***	-0.285***	-0.285***
		(0.008)	(0.006)	(0.006)	(0.008)	(0.008)
Education: some technical (max. low-skilled blue)		0.240***	0.071***	0.077***	0.081***	0.081***
		(0.016)	(0.008)	(0.007)	(0.008)	(0.008)
Education: technical school (max. skilled blue)		0.266***	0.056***	0.060***	0.063***	0.063***
		(0.008)	(0.005)	(0.004)	(0.004)	(0.004)
Education: some tertiary (max. white/professional)		0.505***	0.089***	0.091***	0.095***	0.095***
		(0.016)	(0.005)	(0.004)	(0.004)	(0.004)
Education: tertiary (max. manager top/other)		0.792***	0.217***	0.207***	0.222***	0.222***
		(0.015)	(0.006)	(0.005)	(0.005)	(0.005)
Education: unknown (entrepreneur)		0.364***	0.087***	0.097***	0.090***	0.090***
		(0.014)	(0.006)	(0.004)	(0.004)	(0.004)
Regional Unemp. Rate %		-1.057***	-0.924***	-0.945***	-1.143***	-1.143***
		(0.082)	(0.073)	(0.072)	(0.078)	(0.078)
Roma 5-10% zipcode		-0.060***	-0.025***	-0.020***	-0.026***	-0.026***
		(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
Roma 10%+ zipcode		-0.085***	-0.038***	-0.029***	-0.036***	-0.036***
		(0.009)	(0.005)	(0.006)	(0.007)	(0.007)
Tenure on Job (Month)			0.002***	0.002***	0.003***	0.003***
			(0.000)	(0.000)	(0.000)	(0.000)
Occupation: Other manager			-0.062***	-0.103***	-0.060***	-0.060***
			(0.013)	(0.012)	(0.010)	(0.010)
Occupation: Professional			-0.062***	-0.143***	-0.067***	-0.067***
			(0.019)	(0.018)	(0.014)	(0.014)
Occupation: White Collar			-0.413***	-0.492***	-0.385***	-0.385***
			(0.015)	(0.015)	(0.009)	(0.009)
Occupation: killed Blue Collar			-0.561***	-0.651***	-0.569***	-0.569***
			(0.016)	(0.016)	(0.009)	(0.009)
Occupation: Low-Skilled Blue			-0.629***	-0.714***	-0.636***	-0.636***
			(0.018)	(0.018)	(0.014)	(0.014)
Occupation: Unskilled			-0.782***	-0.840***	-0.738***	-0.738***
			(0.022)	(0.017)	(0.008)	(0.008)
Occupation: Unknown:entrepreneur			-0.194***	-0.061***	-0.206***	-0.206***
			(0.021)	(0.022)	(0.024)	(0.024)

Continued on the next page!

VARIABLES	(1) lwage_rmd	(2) Ln(Daily RWage)	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)	(6) Ln(Daily RWage)
Employment Type: Public Sector				-0.224***	-0.462***	-0.462***
				(0.020)	(0.046)	(0.046)
Employment Type: Public Work Program				-0.345***	-0.175***	-0.175***
				(0.019)	(0.008)	(0.008)
Employment Type: Temp. Contract				0.033	0.152***	0.152***
				(0.021)	(0.016)	(0.016)
Employment Type: Entrepreneur				0.032	-0.641***	-0.641***
				(0.020)	(0.039)	(0.039)
Employment Type: Other				-0.947***	-0.638***	-0.638***
				(0.032)	(0.036)	(0.036)
Firm Size: 10-50					0.045***	0.045***
					(0.001)	(0.001)
Firm Size: 50-250					0.068***	0.068***
					(0.003)	(0.003)
Firm Size: 250+					0.064***	0.064***
					(0.006)	(0.006)
Firm Revenue (Real, HUF)					0.000**	0.000**
					(0.000)	(0.000)
Firm Value Added (Real, HUF)					0.000***	0.000***
					(0.000)	(0.000)
Firm K/L ratio					0.000**	0.000***
					(0.000)	(0.000)
Firm Industry: Mining					0.094***	
					(0.036)	
Firm Industry: Manufacturing					0.027***	
					(0.010)	
Firm Industry: Electricity, water, waste					0.047**	
					(0.021)	
Firm Industry: Construction					0.041***	
					(0.011)	
Firm Industry: Trade					0.025**	
					(0.010)	
Firm Industry: Hotel					0.032***	
					(0.012)	
Firm Industry: Transport, post					0.024	
					(0.017)	
Firm Industry: Finance					0.047**	
					(0.021)	
Firm Industry: Real estate					0.037***	
					(0.011)	
Firm Industry: IT, RD					0.007	
					(0.015)	
Firm Industry: Public: govt, health, educ					0.022*	
					(0.013)	
Firm Industry: Other					0.026**	
					(0.011)	
Fixed Effects (reghdfe)	Year	Year	Year	Year	Year	Year
Fixed Effects (reghdfe)	Firm	Firm	Firm	Firm	Firm	Firm
Abs. Difference After-Before	0.025	0.017	-0.047*	-0.043*	-0.043*	-0.043*
After = Before, F-test 2-sided p	0.065	0.091	0.122	0.000	0.000	0.000
After >Before, F-test 1-sided p	0.033	0.046	0.061	0.000	0.000	0.000
Abs. Difference Total After- Total Before	0.071	0.011	-0.026*	-0.022*	-0.029*	-0.029*
After + First After = Before + Last Before, 2 sided p	0.000	0.112	0.066	0.062	0.068	0.068
After + First After >Before + Last Before, 1-sided p	0.000	0.055	0.033	0.031	0.034	0.034
Observations	183,141,198	181,050,373	177,389,998	177,389,998	109,029,723	109,029,723
R-squared	0.579	0.631	0.698	0.705	0.683	0.683

Clustered standard errors in parentheses: firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Baselines for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode
Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture

Table 31: IV. Wage Regression: Convicts Who Work Before and After Prison and Colleagues

	(1) Raw Employed	(2) Controlled Employed	(3) Raw Ln(Daily RWage)	(4) Controlled Ln(Daily RWage)	(5) Controlled Ln(Daily RWage)	(6) Within Firm, R. Ln(Daily RWage)	(7) Within Firm, C. Ln(Daily RWage)	(8) Within Firm, C. Ln(Daily RWage)
Convict & Before Prison	-0.120***	-0.100***	-0.238***	-0.186***	-0.101***	-0.048***	-0.038***	-0.048***
	(0.002)	(0.002)	(0.025)	(0.023)	(0.021)	(0.017)	(0.013)	(0.016)
Convict & After Prison	-0.190***	-0.172***	-0.331***	-0.192***	-0.102***	-0.063***	-0.010	-0.007
	(0.002)	(0.002)	(0.023)	(0.023)	(0.021)	(0.016)	(0.013)	(0.015)
Prison Spell Length (Month)	0.001***	0.001***	-0.003***	-0.001*	-0.001*	-0.002***	-0.001**	-0.001**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.066***	-0.063***	-0.081***	-0.031**	-0.047***	-0.079***	-0.042***	-0.045***
	(0.001)	(0.001)	(0.013)	(0.013)	(0.014)	(0.010)	(0.009)	(0.011)
Age	0.079***	0.076***	0.080***	0.026***	0.032***	0.062***	0.024***	0.028***
	(0.000)	(0.000)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Age Squared	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.019***	0.015***	0.101***	0.241***	0.258***	0.136***	0.167***	0.197***
	(0.000)	(0.000)	(0.017)	(0.012)	(0.008)	(0.014)	(0.006)	(0.005)
Ln(Real Health Expenditure)		0.012***		-0.003***	-0.007***		-0.009***	-0.010***
		(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Receives Care Allowance		-0.506***		-0.483***	-0.421***		-0.412***	-0.368***
		(0.000)		(0.010)	(0.017)		(0.012)	(0.016)
Receives Disability Pension		-0.375***		-0.446***	-0.467***		-0.285***	-0.261***
		(0.000)		(0.013)	(0.029)		(0.009)	(0.014)
Education: some technical (max. low-skilled blue)		0.197***		0.044***	0.108***		0.061***	0.072***
		(0.000)		(0.016)	(0.017)		(0.012)	(0.014)
Education: technical school (max. skilled blue)		0.177***		0.035***	0.075***		0.040***	0.051***
		(0.000)		(0.008)	(0.010)		(0.005)	(0.006)
Education: some tertiary (max. white/professional)		0.240***		0.032***	0.124***		0.074***	0.086***
		(0.000)		(0.011)	(0.020)		(0.005)	(0.007)
Education: tertiary (max. manager top/other)		0.299***		0.130***	0.232***		0.195***	0.226***
		(0.000)		(0.011)	(0.012)		(0.007)	(0.007)
Education: unknown (entrepreneur)		0.095***		-0.088***	0.056***		0.065***	0.066***
		(0.000)		(0.010)	(0.010)		(0.005)	(0.006)
Regional Unemp Rate %		-0.581***		-1.744***	-2.117***		-0.957***	-1.219***
		(0.001)		(0.224)	(0.169)		(0.103)	(0.107)
Roma 5-10% zipcode		-0.040***		-0.047***	-0.058***		-0.016***	-0.024***
		(0.000)		(0.009)	(0.007)		(0.005)	(0.003)
Roma 10%+ zipcode		-0.059***		-0.056***	-0.070***		-0.026***	-0.038***
		(0.000)		(0.009)	(0.010)		(0.007)	(0.009)
Tenure on Job (Month)				0.004***	0.003***		0.002***	0.003***
				(0.000)	(0.000)		(0.000)	(0.000)
Occupation: Other manager				-0.100***	-0.098**		-0.209***	-0.208***
				(0.026)	(0.048)		(0.028)	(0.060)
Occupation: Professional				-0.134***	0.031		-0.282***	-0.215***
				(0.035)	(0.045)		(0.026)	(0.058)
Occupation: White Collar				-0.494***	-0.443***		-0.659***	-0.602***
				(0.024)	(0.040)		(0.023)	(0.055)
Occupation: Skilled Blue Collar				-0.887***	-0.754***		-0.862***	-0.821***
				(0.026)	(0.039)		(0.025)	(0.056)
Occupation: Low-Skilled Blue				-0.766***	-0.740***		-0.922***	-0.883***
				(0.028)	(0.042)		(0.029)	(0.058)
Occupation: Unskilled				-1.074***	-0.945***		-1.032***	-0.980***
				(0.030)	(0.039)		(0.024)	(0.055)
Occupation: Unknown:entrepreneur				0.043	-0.259***		0.108**	-0.312**
				(0.046)	(0.088)		(0.043)	(0.134)

Continued on the next page!

	(1) Raw Employed	(2) Controlled Employed	(3) Raw Ln(Daily RWage)	(4) Controlled Ln(Daily RWage)	(5) Controlled Ln(Daily RWage)	(6) Within Firm, R. Ln(Daily RWage)	(7) Within Firm, C. Ln(Daily RWage)	(8) Within Firm, C. Ln(Daily RWage)
Employment Type: Public Sector				0.063**	-0.425***		0.213***	-0.471***
				(0.027)	(0.093)		(0.022)	(0.093)
Employment Type: Public Work Program				0.184***	-0.774***		0.063***	-0.625***
				(0.030)	(0.099)		(0.019)	(0.043)
Employment Type: Temp. Contract				-0.484***	0.054		-0.199***	0.049
				(0.041)	(0.034)		(0.023)	(0.041)
Employment Type: Entrepreneur				-1.327***	-0.456***		-0.592***	-0.330***
				(0.047)	(0.018)		(0.021)	(0.018)
Employment Type: Other				-1.449***	-0.744***		-0.956***	-0.762***
				(0.084)	(0.079)		(0.075)	(0.102)
Firm Size: 10-50					0.209***			0.037***
					(0.004)			(0.002)
Firm Size: 50-250					0.411***			0.063***
					(0.008)			(0.004)
Firm Size: 250+					0.574***			0.065***
					(0.014)			(0.007)
Firm Revenue (Real, HUF)					0.000***			0.000**
					(0.000)			(0.000)
Firm Value Added (Real, HUF)					0.000*			0.000***
					(0.000)			(0.000)
Firm K/L ratio					0.000**			0.000**
					(0.000)			(0.000)
Firm Industry: Mining					0.396***			0.090**
					(0.064)			(0.041)
Firm Industry: Manufacturing					0.134***			0.040**
					(0.016)			(0.017)
Firm Industry: Electricity, water, waste					0.257***			0.043
					(0.039)			(0.027)
Firm Industry: Construction					0.053***			0.062***
					(0.020)			(0.020)
Firm Industry: Trade					-0.011			0.039**
					(0.023)			(0.018)
Firm Industry: Hotel					-0.047*			0.049**
					(0.024)			(0.020)
Firm Industry: Transport, post					0.073			0.036
					(0.055)			(0.031)
Firm Industry: Finance					0.413***			0.043
					(0.072)			(0.027)
Firm Industry: Real estate					0.020			0.046***
					(0.019)			(0.018)
Firm Industry: IT, RD					0.265***			-0.003
					(0.045)			(0.022)
Firm Industry: Public: govt, health, educ					0.012			0.049*
					(0.019)			(0.026)
Firm Industry: Other					0.012			0.030
					(0.019)			(0.018)
Observations	176,066,731	173,558,714	103,886,378	100,443,009	58,300,511	103,867,709	100,424,404	58,294,072
R-squared	0.137	0.247	0.050	0.397	0.471	0.501	0.687	0.678
Cluster	-	-	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID
Abs. Diff.: After-Before	.0698	.072	.093	.006	.001	.015	-.028*	-.041*
After = Before F-test 2-sided p	.000	.000	.000	.385	.550	.180	.090	.060
After >Before F-test 1-sided p	.000	.000	.000	.193	.250	.090	.045	.030

Robust and Clustered standard errors in parentheses. Clustering is done by firm ID in the models marked. *** p<0.01, ** p<0.05, * p<0.1
Full regression results are available in the Appendix, Table 31
Baselines for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode
Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture

Table 32: V. Wage Regression with Those Having No Criminal History

	(1) Raw Employed	(2) Controlled Employed	(3) Raw Ln(Daily RWage)	(4) Controlled Ln(Daily RWage)	(5) Controlled Ln(Daily RWage)	(6) Within Firm, R. Ln(Daily RWage)	(7) Within Firm, C. Ln(Daily RWage)	(8) Within Firm, C. Ln(Daily RWage)
Convict & Before Prison	-0.260***	-0.210***	-0.309***	-0.190***	-0.091***	-0.124***	-0.054***	-0.064***
	(0.001)	(0.001)	(0.014)	(0.012)	(0.011)	(0.011)	(0.006)	(0.008)
Convict & After Prison	-0.321***	-0.272***	-0.410***	-0.201***	-0.093***	-0.144***	-0.018**	-0.018**
	(0.001)	(0.001)	(0.018)	(0.017)	(0.013)	(0.013)	(0.009)	(0.009)
Prison Spell Length (Month)	0.001***	0.001***	-0.000	-0.001	-0.001*	-0.000	-0.000	-0.001**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.049***	-0.044***	-0.056***	-0.040***	-0.044***	-0.048***	-0.036***	-0.040***
	(0.000)	(0.000)	(0.007)	(0.007)	(0.008)	(0.006)	(0.005)	(0.006)
Age	0.079***	0.077***	0.082***	0.027***	0.033***	0.063***	0.025***	0.029***
	(0.000)	(0.000)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Age Squared	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.022***	0.016***	0.099***	0.239***	0.257***	0.140***	0.168***	0.196***
	(0.000)	(0.000)	(0.016)	(0.011)	(0.008)	(0.012)	(0.005)	(0.005)
Ln(Real Health Expenditure)		0.012***		-0.003***	-0.007***		-0.009***	-0.009***
		(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Receives Care Allowance		-0.506***		-0.479***	-0.418***		-0.409***	-0.369***
		(0.000)		(0.009)	(0.015)		(0.011)	(0.014)
Receives Disability Pension		-0.375***		-0.447***	-0.465***		-0.281***	-0.257***
		(0.000)		(0.011)	(0.025)		(0.008)	(0.012)
Education (approx) = 2, Education: some technical (max. low-skilled blue)		0.193***		0.051***	0.111***		0.065***	0.074***
		(0.000)		(0.014)	(0.015)		(0.010)	(0.012)
Education (approx) = 3, Education: technical school (max. skilled blue)		0.169***		0.035***	0.075***		0.044***	0.051***
		(0.000)		(0.007)	(0.008)		(0.004)	(0.006)
Education (approx) = 4, Education: some tertiary (max. white/professional)		0.231***		0.040***	0.124***		0.077***	0.085***
		(0.000)		(0.011)	(0.018)		(0.004)	(0.006)
Education (approx) = 5, Education: tertiary (max. manager top/other)		0.290***		0.130***	0.228***		0.197***	0.224***
		(0.000)		(0.010)	(0.011)		(0.006)	(0.006)
Education (approx) = 6, Education: unknown (entrepreneur)		0.098***		-0.076***	0.061***		0.071***	0.068***
		(0.000)		(0.009)	(0.009)		(0.004)	(0.005)
Regional Unemp Rate %		-0.518***		-1.748***	-2.043***		-0.972***	-1.215***
		(0.001)		(0.222)	(0.164)		(0.092)	(0.096)
Roma 5-10% zipcode		-0.036***		-0.049***	-0.060***		-0.017***	-0.025***
		(0.000)		(0.009)	(0.007)		(0.004)	(0.003)
Roma 10%+ zipcode		-0.059***		-0.056***	-0.071***		-0.025***	-0.034***
		(0.000)		(0.009)	(0.010)		(0.006)	(0.009)
Tenure on Job (Month)				0.004***	0.003***		0.002***	0.003***
				(0.000)	(0.000)		(0.000)	(0.000)
Occupation: Other manager				-0.080***	-0.091**		-0.202***	-0.191***
				(0.023)	(0.037)		(0.024)	(0.043)
Occupation: Professional				-0.094***	0.043		-0.274***	-0.206***
				(0.036)	(0.035)		(0.023)	(0.042)
Occupation: White Collar				-0.467***	-0.430***		-0.651***	-0.581***
				(0.023)	(0.031)		(0.020)	(0.039)
Occupation: Skilled Blue Collar				-0.864***	-0.746***		-0.849***	-0.798***
				(0.024)	(0.030)		(0.022)	(0.040)
Occupation: Low-Skilled Blue				-0.744***	-0.734***		-0.905***	-0.856***
				(0.026)	(0.032)		(0.025)	(0.042)
Occupation: Unskilled				-1.055***	-0.941***		-1.020***	-0.957***
				(0.027)	(0.030)		(0.021)	(0.039)
Occupation: Unknown:entrepreneur				0.032	-0.246***		0.078*	-0.313***
				(0.039)	(0.067)		(0.040)	(0.102)
Occupation: Public Sector				0.066**	-0.366***		0.216***	-0.386***
				(0.026)	(0.096)		(0.022)	(0.104)
Occupation: Public Work Program				0.196***	-0.771***		0.059***	-0.626***
				(0.029)	(0.099)		(0.019)	(0.042)
Occupation: Temp. Contract				-0.459***	0.053*		-0.176***	0.060*
				(0.038)	(0.029)		(0.023)	(0.035)
Occupation: Entrepreneur				-1.282***	-0.451***		-0.557***	-0.309***
				(0.042)	(0.015)		(0.020)	(0.015)
Occupation: Other				-1.325***	-0.650***		-0.920***	-0.702***
				(0.075)	(0.066)		(0.062)	(0.081)

Continued on the next page!

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Raw	Controlled	Raw	Controlled	Controlled	Within Firm, R.	Within Firm, C.	Within Firm, C.
	Employed	Employed	Ln(Daily RWage)	Ln(Daily RWage)	Ln(Daily RWage)	Ln(Daily RWage)	Ln(Daily RWage)	Ln(Daily RWage)
Employment Type: Public Sector				0.062**	-0.425***		0.212***	-0.470***
				(0.0276)	(0.092)		(0.022)	(0.093)
Employment Type: Public Work Program				0.181***	-0.774***		0.062***	-0.626***
				(0.031)	(0.099)		(0.019)	(0.042)
Employment Type: Temp. Contract				-0.464***	0.061		-0.196***	0.041
				(0.040)	(0.033)		(0.023)	(0.041)
Employment Type: Entrepreneur				-0.998***	-0.456***		-0.592***	-0.330***
				(0.047)	(0.018)		(0.021)	(0.018)
Employment Type: Other				-1.321***	-0.746***		-0.954***	-0.761***
				(0.08‘)	(0.077)		(0.072)	(0.101)
Firm Size: 10-50					0.217***			0.040***
					(0.004)			(0.002)
Firm Size: 50-250					0.427***			0.066***
					(0.008)			(0.004)
Firm Size: 250+					0.588***			0.068***
					(0.015)			(0.007)
Firm Industry: Mining					0.369***			0.099***
					(0.057)			(0.036)
Firm Industry: Manufacturing					0.120***			0.036**
					(0.015)			(0.015)
Firm Industry: Electricity, water, waste					0.263***			0.048*
					(0.039)			(0.026)
Firm Industry: Construction					0.037**			0.058***
					(0.017)			(0.017)
Firm Industry: Trade					-0.013			0.035**
					(0.022)			(0.016)
Firm Industry: Hotel					-0.067***			0.045**
					(0.022)			(0.018)
Firm Industry: Transport, post					0.054			0.033
					(0.056)			(0.027)
Firm Industry: Finance					0.389***			0.043*
					(0.061)			(0.025)
Firm Industry: Real estate					0.006			0.047***
					(0.018)			(0.016)
Firm Industry: IT, RD					0.254***			0.012
					(0.039)			(0.021)
Firm Industry: Public: govt, health, educ					-0.002			0.041*
					(0.020)			(0.022)
Firm Industry: Other					0.003			0.033**
					(0.018)			(0.016)
Firm Revenue (Real, HUF)					0.000***			0.000***
					(0.000)			(0.000)
Firm Value Added (Real, HUF)					0.000**			0.000***
					(0.000)			(0.000)
Firm K/L ratio					0.000***			0.000**
					(0.000)			(0.000)
Observations	201,631,923	198,709,946	118,483,839	114,509,511	68,761,109	118,464,615	114,490,361	68,754,795
R-squared	0.144	0.249	0.051	0.391	0.475	0.518	0.691	0.685
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year
Fixed Effects	-	-	-	-	-	Firm	Firm	Firm
Cluster	-	-	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID
Abs. Diff.: After-Before	.061	.062	.101	.011	.002	.020	-.036*	-.046*
After = Before F-test 2-sided p	0.000	0.000	0.000	.016	.396	.031	0.000	0.000
After >Before F-test 1-sided p	0.000	0.000	0.000	.081	.198	.016	0.000	0.000

Robust and Clustered standard errors in parentheses. Clustering is done by firm ID in the models marked. *** p<0.01, ** p<0.05, * p<0.1

Baselines for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode

Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture

Table 33: VI. Wage Regression for Men with No Education

	(1) Raw Employed	(2) Controlled Employed	(3) Raw Ln(Daily RWage)	(4) Controlled Ln(Daily RWage)	(5) Controlled Ln(Daily RWage)	(6) Within Firm, R. Ln(Daily RWage)	(7) Within Firm, C. Ln(Daily RWage)	(8) Within Firm, C. Ln(Daily RWage)
Convict & Before Prison	-0.114***	-0.115***	-0.289***	-0.120***	-0.105***	-0.112***	-0.069***	-0.066***
	(0.000)	(0.000)	(0.024)	(0.020)	(0.021)	(0.011)	(0.009)	(0.014)
Convict & After Prison	-0.139***	-0.137***	-0.348***	-0.173**	-0.111**	-0.178***	-0.009*	-0.022**
	(0.001)	(0.000)	(0.027)	(0.033)	(0.030)	(0.013)	(0.014)	(0.015)
Prison Spell Length (Month)	0.000***	0.001***	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Prison Spells	-0.020***	-0.007***	-0.054***	-0.037***	-0.056***	-0.036***	-0.031***	-0.035***
	(0.000)	(0.000)	(0.009)	(0.009)	(0.013)	(0.005)	(0.005)	(0.010)
Age	0.024***	0.007***	0.057***	0.023***	0.029***	0.030***	0.020***	0.023***
	(0.000)	(0.000)	(0.005)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)
Age Squared	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Real Health Expenditure)		0.003***		0.003***	-0.004***		-0.008***	-0.009***
		(0.000)		(0.001)	(0.000)		(0.000)	(0.000)
Receives Care Allowance		-0.124***		-0.344***	-0.269***		-0.181***	-0.170***
		(0.000)		(0.023)	(0.023)		(0.016)	(0.019)
Receives Disability Pension		-0.061***		-0.342***	-0.356***		-0.188***	-0.171***
		(0.000)		(0.016)	(0.022)		(0.008)	(0.009)
Education: none (always unskilled)		0.271***						
		(0.000)						
Education: some technical (max. low-skilled blue)		0.623***		0.105***	0.100***		0.067***	0.078***
		(0.000)		(0.009)	(0.008)		(0.005)	(0.006)
Regional Unemp Rate %		-0.041***		-0.722	-0.919***		-0.438***	-0.504***
		(0.001)		(0.505)	(0.305)		(0.093)	(0.084)
Roma 5-10% zipcode		-0.007***		-0.056***	-0.049***		-0.016**	-0.022***
		(0.000)		(0.015)	(0.011)		(0.006)	(0.007)
Roma 10%+ zipcode		-0.016***		-0.066***	-0.091***		-0.023**	-0.036***
		(0.000)		(0.016)	(0.016)		(0.010)	(0.012)
Tenure on Job (Month)				0.005***	0.003***		0.001***	0.002***
				(0.000)	(0.000)		(0.000)	(0.000)
Occupation: Unskilled				-0.314***	-0.225***		-0.200***	-0.187***
				(0.024)	(0.010)		(0.009)	(0.011)
Employment Type: Public Sector				-0.260***	-0.213*		-0.266***	-0.132
				(0.063)	(0.113)		(0.020)	(0.123)
Employment Type: Public Work Program				-0.455***	-0.683***		-0.103***	-0.563***
				(0.042)	(0.103)		(0.030)	(0.044)
Employment Type: Temp. Contract				-0.177***	-0.052		-0.017	-0.009
				(0.057)	(0.061)		(0.056)	(0.062)
Employment Type: Entrepreneur				-0.098***	-0.004		0.148***	0.158**
				(0.045)	(0.045)		(0.054)	(0.065)
Employment Type: Other				-0.062**	0.067***		0.005	0.006
				(0.028)	(0.019)		(0.014)	(0.014)
Firm Size: 10-50					0.167***			0.026***
					(0.007)			(0.003)
Firm Size: 50-250					0.366***			0.049***
					(0.014)			(0.007)
Firm Size: 250+					0.570***			0.068***
					(0.029)			(0.010)
Firm Industry: Mining					0.209***			0.031
					(0.042)			(0.064)
Firm Industry: Manufacturing					0.011			0.031
					(0.017)			(0.019)
Firm Industry: Electricity, water, waste					0.153***			0.072**
					(0.037)			(0.030)
Firm Industry: Construction					0.050***			0.047**
					(0.015)			(0.021)
Firm Industry: Trade					-0.074***			0.036
					(0.016)			(0.023)
Firm Industry: Hotel					-0.249***			0.018
					(0.031)			(0.041)
Firm Industry: Transport, post					0.038			0.009
					(0.032)			(0.028)
Firm Industry: Finance					0.118**			0.030
					(0.054)			(0.055)
Firm Industry: Real estate					-0.085***			0.032
					(0.027)			(0.025)
Firm Industry: IT, RD					-0.075			-0.046
					(0.072)			(0.062)
Firm Industry: Public: govt, health, educ					-0.106***			0.028
					(0.025)			(0.025)
Firm Industry: Other					-0.072***			0.024
					(0.024)			(0.020)
Firm Revenue (Real, HUF)					0.000***			0.000*
					(0.000)			(0.000)
Firm Value Added (Real, HUF)					0.000***			0.000**
					(0.000)			(0.000)
Firm K/L ratio					0.000***			0.000
					(0.000)			(0.000)
Observations	22,371,085	21,853,346	11,110,575	10,931,942	8,374,116	11,106,785	10,928,213	8,372,018
R-squared	0.159	0.289	0.034	0.251	0.444	0.712	0.744	0.752
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year
Fixed Effects	-	-	-	-	-	Firm	Firm	Firm
Cluster	-	-	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID	Firm ID
Abs. Diff.: After-Before	.025	.022	.059	.053	.006	.066	-.060*	-.044*
After = Before F-test 2-sided p	.024	.029	.008	.007	.165	.004	.004	.012
After >Before F-test 1-sided p	.012	.014	.004	.003	.083	.002	.002	.006

Robust and Clustered standard errors in parentheses. Clustering is done by firm ID in the models marked. *** p<0.01, ** p<0.05, * p<0.1.
Baseline for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode, Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture

Table 34: Balancing Tests: Nearest Neighbour 1 - 1 Year

Variable	Unmatched Matched	Mean Treated	Mean Control	t-test t	t-test p>|t|
Age	U	30.857	38.083	-55.840	0.000
	M	30.857	30.682	1.070	0.284
Male	U	.92442	.51752	68.150	0.000
	M	.92442	.91372	2.320	0.020
Regional Unemp Rate %	U	.06045	.05819	9.920	0.000
	M	.06045	.06038	0.210	0.836
Receives Care Allowance	U	.01226	.01697	-3.60	0.000
	M	.01226	.01217	0.06	0.953
Receives Disability Pension	U	.00535	.00679	-1.55	0.120
	M	.00535	.00593	-0.49	0.627
Employed Months (of 12)	U	7.1586	10.492	-90.91	0.000
	M	7.1586	7.0693	1.22	0.221
Days Worked/Month	U	28.798	30.026	-63.37	0.000
	M	28.798	28.789	0.14	0.889
Education: some technical (max. low-skilled blue)	U	.07587	.06458	3.84	0.000
	M	.07587	.06817	1.76	0.078
Education: technical school (max. skilled blue)	U	.33485	.24527	17.40	0.000
	M	.33485	.32159	1.67	0.094
Education: some tertiary (max. white/professional)	U	.08443	.28815	-37.64	0.000
	M	.08443	.09213	-1.61	0.108
Education: tertiary (max. manager top/other)	U	.08514	.09951	-4.01	0.000
	M	.08514	.08614	-0.21	0.833
Education: unknown (entrepreneur)	U	.29079	.24724	8.44	0.000
	M	.29079	.30006	-1.20	0.229
Occupation: Other manager	U	.04735	.05979	-4.39	0.000
	M	.04735	.04949	-0.59	0.555
Occupation: Professional	U	.02196	.10951	-23.47	0.000
	M	.02196	.02253	-0.23	0.819
Occupation: White Collar	U	.06303	.20485	-29.40	0.000
	M	.06303	.06332	-0.07	0.945
Occupation: Skilled Blue Collar	U	.33614	.31158	4.43	0.000
	M	.33614	.32844	0.97	0.333
Occupation: Low-Skilled Blue	U	.14233	.10573	9.94	0.000
	M	.14233	.13306	1.59	0.111
Occupation: Unskilled	U	.30676	.11664	49.41	0.000
	M	.30676	.31845	-1.49	0.135
Occupation: Unknown:entrepreneur	U	.06232	.07522	-4.09	0.000
	M	.06232	.06403	-0.42	0.677
Real Monthly Wage	U	1.0e+05	1.6e+05	-35.40	0.000
	M	1.0e+05	1.0e+05	-0.37	0.712
Firm Size	U	4393.3	5221.9	-5.98	0.000
	M	4393.3	4464.1	-0.40	0.687
Firm Industry: Mining	U	.00314	.00176	2.74	0.006
	M	.00314	.00428	-1.11	0.266
Firm Industry: Manufacturing	U	.21449	.21416	0.07	0.946
	M	.21449	.20764	0.99	0.321
Firm Industry: Electricity, water, waste	U	.02467	.02235	1.31	0.189
	M	.02467	.02225	0.95	0.343
Firm Industry: Construction	U	.07929	.04156	15.78	0.000
	M	.07929	.07116	1.82	0.068
Firm Industry: Trade	U	.10011	.10908	-2.40	0.016
	M	.10011	.09983	0.06	0.955
Firm Industry: Hotel	U	.02453	.02017	2.59	0.010
	M	.02453	.02467	-0.05	0.957
Firm Industry: Transport, post	U	.05476	.06535	-3.58	0.000
	M	.05476	.05833	-0.91	0.361
Firm Industry: Finance	U	.00627	.01574	6.36	0.000
	M	.00627	.00642	-0.11	0.915
Firm Industry: Real estate	U	.01697	.01276	3.14	0.002
	M	.01697	.01583	0.53	0.595
Firm Industry: IT, RD	U	.00385	.00895	-4.53	0.000
	M	.00385	.00314	0.72	0.474
Firm Industry: Public: govt, health, educ	U	.02082	.01554	3.56	0.000
	M	.02082	.01854	0.97	0.331
Firm Industry: Other	U	.07173	.04987	8.39	0.000
	M	.07173	.07302	-0.29	0.769
Frim Industry: Small Enterprise	U	.34669	.39094	-7.58	0.000
	M	.34669	.36295	-2.01	0.044
Sample	Ps_R2	LR_chi2	p>chi2	MeanBias	MedBias
Unmatched	0.154	14192.63	0.000	20.700	8.300
Matched	0.002	33.88	0.474	1.400	1.200

Table 35: Balancing Tests: Nearest Neighbour 10 - 1 Year

Variable	Unmatched Matched	Mean Treated	Mean Control	t-test t	t-test p>|t|
Age	U	30.857	38.083	-55.840	0.000
	M	30.857	30.566	1.790	0.073
Male	U	.92442	.51752	68.150	0.000
	M	.92442	.91367	2.330	0.020
Regional Unemp Rate %	U	.06045	.05819	9.920	0.000
	M	.06045	.06026	0.600	0.551
Receives Care Allowance	U	.01226	.01697	-3.600	0.000
	M	.01226	.01089	0.880	0.381
Receives Disability Pension	U	.00535	.00679	-1.550	0.120
	M	.00535	.0054	-0.050	0.964
Employed Months (of 12)	U	7.1586	10.492	-90.910	0.000
	M	7.1586	7.0889	0.960	0.339
Days Worked/Month	U	28.798	30.026	-63.370	0.000
	M	28.798	28.766	0.530	0.599
Education: some technical (max. low-skilled blue)	U	.07587	.06458	3.840	0.000
	M	.07587	.06987	1.370	0.172
Education: technical school (max. skilled blue)	U	.33485	.24527	17.400	0.000
	M	.33485	.32138	1.700	0.089
Education: some tertiary (max. white/professional)	U	.08443	.28815	-37.640	0.000
	M	.08443	.09245	-1.670	0.094
Education: tertiary (max. manager top/other)	U	.08514	.09951	-4.010	0.000
	M	.08514	.08618	-0.220	0.826
Education: unknown (entrepreneur)	U	.29079	.24724	8.440	0.000
	M	.29079	.30286	-1.560	0.118
Occupation: Other manager	U	.04735	.05979	-4.390	0.000
	M	.04735	.04772	-0.100	0.916
Occupation: Professional	U	.02196	.10951	-23.470	0.000
	M	.02196	.02339	-0.570	0.571
Occupation: White Collar	U	.06303	.20485	-29.400	0.000
	M	.06303	.06881	-1.380	0.168
Occupation: Skilled Blue Collar	U	.33614	.31158	4.430	0.000
	M	.33614	.32301	1.650	0.098
Occupation: Low-Skilled Blue	U	.14233	.10573	9.940	0.000
	M	.14233	.13567	1.140	0.254
Occupation: Unskilled	U	.30676	.11664	49.410	0.000
	M	.30676	.31148	-0.600	0.546
Occupation: Unknown:entrepreneur	U	.06232	.07522	-4.090	0.000
	M	.06232	.06912	-1.620	0.104
Real Monthly Wage	U	1.0e+05	1.6e+05	-35.400	0.000
	M	1.0e+05	1.0e+05	0.080	0.936
Firm Size	U	4393.3	5221.9	-5.980	0.000
	M	4393.3	4350.3	0.250	0.805
Firm Industry: Mining	U	.00314	.00176	2.740	0.006
	M	.00314	.00284	0.330	0.743
Firm Industry: Manufacturing	U	.21449	.21416	0.070	0.946
	M	.21449	.20554	1.300	0.193
Firm Industry: Electricity, water, waste	U	.02467	.02235	1.310	0.189
	M	.02467	.02276	0.740	0.457
Firm Industry: Construction	U	.07929	.04156	15.780	0.000
	M	.07929	.07888	0.090	0.927
Firm Industry: Trade	U	.10011	.10908	-2.400	0.016
	M	.10011	.10131	-0.230	0.815
Firm Industry: Hotel	U	.02453	.02017	2.590	0.010
	M	.02453	.02555	-0.390	0.698
Firm Industry: Transport, post	U	.05476	.06535	-3.580	0.000
	M	.05476	.05391	0.220	0.824
Firm Industry: Finance	U	.00627	.01574	-6.360	0.000
	M	.00627	.00693	-0.480	0.630
Firm Industry: Real estate	U	.01697	.01276	3.140	0.002
	M	.01697	.01736	-0.180	0.861
Firm Industry: IT, RD	U	.00385	.00895	-4.530	0.000
	M	.00385	.00384	0.010	0.996
Firm Industry: Public: govt, health, educ	U	.02082	.01554	3.560	0.000
	M	.02082	.02097	-0.060	0.951
Firm Industry: Other	U	.07173	.04987	8.390	0.000
	M	.07173	.07277	-0.240	0.813
Frim Industry: Small Enterprise	U	.34669	.39094	-7.580	0.000
	M	.34669	.356	-1.160	0.248
Sample	**Ps_R2**	**LR_chi2**	**p>chi2**	**MeanBias**	**MedBias**
Unmatched	0.154	14192.63	0.000	20.70	0.71
Matched	0.001	24.64	0.880	1.2	0.89

Table 36: Balancing Tests: Kernel - 1 Year

Variable	Unmatched Matched	Mean Treated	Mean Control	t-test t	t-test p>|t|
Age	U	30.857	38.083	-55.840	0.000
	M	30.857	30.692	1.080	0.280
Male	U	.92442	.51752	68.150	0.000
	M	.92442	.90301	0.02141	0.004
Regional Unemp Rate %	U	.06045	.05819	9.920	0.000
	M	.06045	.06142	0.192	0.765
Receives Care Allowance	U	.01226	.01697	-3.600	0.000
	M	.01226	.01651	-2.450	0.014
Receives Disability Pension	U	.00535	.00679	-1.550	0.120
	M	.00535	.00668	-1.070	0.285
Employed Months (of 12)	U	7.1586	10.492	-90.910	0.000
	M	7.1586	7.0672	0.0914	0.182
Days Worked/Month	U	28.798	30.026	-63.370	0.000
	M	28.798	29.909	-23.460	0.000
Education: some technical (max. low-skilled blue)	U	.07587	.06458	3.840	0.000
	M	.07587	.06482	2.560	0.010
Education: technical school (max. skilled blue)	U	.33485	.24527	17.400	0.000
	M	.33485	.25131	10.910	0.000
Education: some tertiary (max. white/professional)	U	.08443	.28815	-37.640	0.000
	M	.08443	.2732	-30.090	0.000
Education: tertiary (max. manager top/other)	U	.08514	.09951	-4.010	0.000
	M	.08514	.09806	-2.650	0.008
Education: unknown (entrepreneur)	U	.29079	.24724	8.440	0.000
	M	.29079	.25119	5.280	0.000
Occupation: Other manager	U	.04735	.05979	-4.390	0.000
	M	.04735	.05852	-2.950	0.003
Occupation: Professional	U	.02196	.10951	-23.470	0.000
	M	.02196	.10298	-20.100	0.000
Occupation: White Collar	U	.06303	.20485	-29.400	0.000
	M	.06303	.19444	-23.690	0.000
Occupation: Skilled Blue Collar	U	.33614	.31158	4.430	0.000
	M	.33614	.31192	3.060	0.002
Occupation: Low-Skilled Blue	U	.14233	.10573	9.940	0.000
	M	.14233	.1078	6.190	0.000
Occupation: Unskilled	U	.30676	.11664	49.410	0.000
	M	.30676	.13355	25.310	0.000
Occupation: Unknown:entrepreneur	U	.06232	.07522	-4.090	0.000
	M	.06232	.07397	-2.740	0.006
Real Monthly Wage	U	1.0e+05	1.6e+05	-35.400	0.000
	M	1.0e+05	1.0e+05	-0.37	0.456
Firm Size	U	4393.30	5221.90	-5.980	0.000
	M	4393.30	5172.50	-4.230	0.000
Firm Industry: Mining	U	.00314	.00176	2.740	0.006
	M	.00314	.00185	1.540	0.125
Firm Industry: Manufacturing	U	.21449	.21416	0.070	0.946
	M	.21449	.21356	0.130	0.893
Firm Industry: Electricity, water, waste	U	.02467	.02235	1.310	0.189
	M	.02467	.02238	0.890	0.372
Firm Industry: Construction	U	.07929	.04156	15.780	0.000
	M	.07929	.04445	8.590	0.000
Firm Industry: Trade	U	.10011	.10908	-2.400	0.016
	M	.10011	.10832	-1.590	0.112
Firm Industry: Hotel	U	.02453	.02017	2.590	0.010
	M	.02453	.02053	1.600	0.110
Firm Industry: Transport, post	U	.05476	.06535	-3.580	0.000
	M	.05476	.06428	-2.380	0.017
Firm Industry: Finance	U	.00627	.01574	-6.360	0.000
	M	.00627	.01505	-5.070	0.000
Firm Industry: Real estate	U	.01697	.01276	3.140	0.002
	M	.01697	.01312	1.870	0.061
Firm Industry: IT, RD	U	.00385	.00895	-4.530	0.000
	M	.00385	.00856	-3.560	0.000
Firm Industry: Public: govt, health, educ	U	.02082	.01554	3.560	0.000
	M	.02082	.01603	2.110	0.035
Firm Industry: Other	U	.07173	.04987	8.390	0.000
	M	.07173	.05179	4.910	0.000
Frim Industry: Small Enterprise	U	.34669	.39094	-7.580	0.000
	M	.34669	.38822	-5.110	0.000
Sample	**Ps_R2**	**LR_chi2**	**p>chi2**	**MeanBias**	**MedBias**
Unmatched	0.154	14192.63	0.000	20.70	0.71
Matched	0.261	4510.21	0.065	19.10	0.53

Table 37: VII. Matched Control Group - 1 Year - Nearest Neighbour 1

VARIABLES	(1) Employed	(2) Employed	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)
Convict & Before Prison	-0.183***	-0.182***	0.044**	-0.002	-0.037**
	(0.002)	(0.001)	(0.021)	(0.016)	(0.016)
Convict & After Prison	-0.194***	-0.197***	-0.126***	-0.060***	-0.055***
	(0.002)	(0.002)	(0.026)	(0.020)	(0.020)
Prison Spell Length (Month)	0.000*	0.000***	-0.001	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Number of Prison Spells	-0.079***	-0.068***	-0.055***	-0.042***	-0.030**
	(0.001)	(0.001)	(0.014)	(0.012)	(0.013)
Age	0.053***	0.048***	0.002	0.006**	0.019***
	(0.000)	(0.000)	(0.004)	(0.003)	(0.003)
Age Squared	-0.001***	-0.001***	-0.000	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.035***	0.036***	0.015	0.137***	0.186***
	(0.002)	(0.002)	(0.020)	(0.016)	(0.018)
Ln(Real Health Expenditure)		0.014***		-0.000	-0.004***
		(0.000)		(0.001)	(0.001)
Receives Care Allowance		-0.365***		-0.319***	-0.234***
		(0.003)		(0.045)	(0.042)
Receives Disability Pension		-0.349***		-0.331***	-0.338***
		(0.003)		(0.060)	(0.087)
Education: some technical (max. low-skilled blue)		0.216***		0.092***	0.141***
		(0.002)		(0.023)	(0.027)
Education: technical school (max. skilled blue)		0.200***		0.094***	0.114***
		(0.001)		(0.016)	(0.020)
Education: some tertiary (max. white/professional)		0.305***		0.111***	0.165***
		(0.002)		(0.023)	(0.026)
Education: tertiary (max. manager top/other)		0.326***		0.095***	0.152***
		(0.002)		(0.024)	(0.026)
Education: unknown (entrepreneur)		0.250***		0.006	0.101***
		(0.001)		(0.016)	(0.021)
Regional Unemp. Rate %		-0.564***		-0.892***	-1.460***
		(0.016)		(0.202)	(0.185)
Roma 5-10% zipcode		-0.030***		-0.040***	-0.036***
		(0.001)		(0.013)	(0.013)
Roma 10%+ zipcode		-0.060***		-0.039*	-0.080***
		(0.002)		(0.022)	(0.026)
Tenure on Job (Month)				0.004***	0.003***
				(0.000)	(0.000)
Occupation: Other manager				0.099***	0.065*
				(0.033)	(0.033)
Occupation: Professional				0.288***	0.235***
				(0.045)	(0.045)
Occupation: White Collar				-0.068*	-0.114***
				(0.039)	(0.039)
Occupation: Skilled Blue Collar				-0.330***	-0.372***
				(0.036)	(0.035)
Occupation: Low-Skilled Blue				-0.195***	-0.365***
				(0.037)	(0.038)
Occupation: Unskilled				-0.472***	-0.537***
				(0.037)	(0.037)
Occupation: Unknown:entrepreneur				-0.077**	-0.011
				(0.031)	(0.040)

Robust standard errors are used in estimations (1) and (2). Clustered standard errors in estimations (3)-(6): firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The model is estimated on the time-frame 2004-2011. The matching is based on an exact nearest matching on the common support, with no replacement and ties.

VARIABLES	(1) Employed	(2) Employed	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)
Employment Type = 2, Public Sector				-0.332***	-0.130
				(0.048)	(0.446)
Employment Type = 3, Public Work Program				-0.551***	-0.200***
				(0.035)	(0.084)
Employment Type = 4, Temp. Contract				0.037	0.147***
				(0.043)	(0.057)
Employment Type = 5, Entrepreneur				0.181***	-0.135***
				(0.033)	(0.026)
Employment Type = 6, Other				-0.894***	-0.579***
				(0.166)	(0.168)
Firm Size: 10-50					0.263***
					(0.012)
Firm Size: 50-250					0.459***
					(0.014)
Firm Size: 250+					0.626***
					(0.018)
Firm Industry: Mining					0.356***
					(0.081)
Firm Industry: Manufacturing					0.069***
					(0.024)
Firm Industry: Electricity, water, waste					0.177***
					(0.036)
Firm Industry: Construction					0.027
					(0.025)
Firm Industry: Trade					0.007
					(0.025)
Firm Industry: Hotel					-0.133***
					(0.028)
Firm Industry: Transport, post					0.030
					(0.035)
Firm Industry: Finance					0.417***
					(0.067)
Firm Industry: Real estate					-0.018
					(0.033)
Firm Industry: IT, RD					0.053
					(0.054)
Firm Industry: Public: govt, health, educ					-0.070
					(0.043)
Firm Industry: Other					-0.045
					(0.027)
Firm Revenue (Real, HUF)					0.000*
					(0.000)
Firm Value Added (Real, HUF)					0.000***
					(0.000)
Firm K/L ratio					0.000***
					(0.000)
Observations	1,381,287	1,381,287	737,851	730,289	446,232
R-squared	0.101	0.174	0.025	0.239	0.371
Fixed Effects	Year	Year	Year	Year	Year
Cluster	-	-	Firm	Firm	Firm
Number of Convicts	7012	7012	7012	7012	7012
Number of Non-Convicts	8494	8494	8494	8494	8494
Abs. Diff.: After-Before	.011	.015	.082	.058	.018
After = Before F-test 2-sided p	.021	.020	.000	.000	.018
After >Before F-test 1-sided p	.011	.010	.000	.000	.009

Robust standard errors are used in estimations (1) and (2). Clustered standard errors in estimations (3)-(6): firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The model is estimated on the time-frame 2004-2011. The matching is based on an exact nearest matching on the common support, with no replacement and ties.
Baselines for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode
Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture

Table 38: VII. Matched Control Group - 1 Year - Nearest Neighbour 10

VARIABLES	(1) Employed	(2) Employed	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)
Convict & Before Prison	-0.166***	-0.167***	-0.015	-0.005	-0.046***
	(0.001)	(0.001)	(0.020)	(0.015)	(0.016)
Convict & After Prison	-0.197***	-0.203***	-0.178***	-0.071***	-0.073***
	(0.002)	(0.002)	(0.025)	(0.019)	(0.020)
Prison Spell Length (Month)	0.000***	0.000***	-0.001	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Number of Prison Spells	-0.075***	-0.065***	-0.055***	-0.040***	-0.026**
	(0.001)	(0.001)	(0.014)	(0.012)	(0.013)
Age	0.055***	0.052***	0.023***	0.013***	0.023***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Age Squared	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.039***	0.024***	0.035***	0.158***	0.188***
	(0.001)	(0.001)	(0.013)	(0.011)	(0.008)
Ln(Real Health Expenditure)		0.015***		0.002***	-0.003***
		(0.000)		(0.000)	(0.000)
Receives Care Allowance		-0.452***		-0.418***	-0.339***
		(0.001)		(0.029)	(0.027)
Receives Disability Pension		-0.377***		-0.430***	-0.459***
		(0.001)		(0.029)	(0.037)
Education: some technical (max. low-skilled blue)		0.274***		0.087***	0.110***
		(0.001)		(0.015)	(0.015)
Education: technical school (max. skilled blue)		0.225***		0.074***	0.076***
		(0.001)		(0.009)	(0.011)
Education: some tertiary (max. white/professional)		0.306***		0.110***	0.117***
		(0.001)		(0.011)	(0.016)
Education: tertiary (max. manager top/other)		0.341***		0.114***	0.145***
		(0.001)		(0.014)	(0.013)
Education: unknown (entrepreneur)		0.209***		-0.016	0.059***
		(0.001)		(0.010)	(0.011)
Regional Unemp Rate %		-0.507***		-0.976***	-1.392***
		(0.007)		(0.157)	(0.117)
Roma 5-10% zipcode		-0.048***		-0.027***	-0.029***
		(0.001)		(0.008)	(0.007)
Roma 10%+ zipcode		-0.090***		-0.035***	-0.072***
		(0.001)		(0.010)	(0.013)
Tenure on Job (Month)				0.004***	0.003***
				(0.000)	(0.000)
Occupation: Other manager				0.133***	0.054***
				(0.018)	(0.015)
Occupation: Professional				0.329***	0.270***
				(0.027)	(0.021)
Occupation: White Collar				-0.009	-0.099***
				(0.022)	(0.018)
Occupation: Skilled Blue Collar				-0.309***	-0.370***
				(0.019)	(0.016)
Occupation: Low-Skilled Blue				-0.172***	-0.358***
				(0.021)	(0.019)
Occupation: Unskilled				-0.461***	-0.549***
				(0.022)	(0.017)
Occupation: Unknown:entrepreneur				-0.040**	0.024
				(0.018)	(0.022)

Robust standard errors are used in estimations (1) and (2). Clustered standard errors in estimations (3)-(6): firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The model is estimated on the time-frame 2004-2011. The matching is based on an k-nearest matching (with 10 neighbours) on the common support, with no replacement and ties.

VARIABLES	(1) Employed	(2) Employed	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)
Employment Type: Public Sector				-0.257***	-0.016
				(0.046)	(0.118)
Employment Type: Public Work Program				-0.574***	-0.227***
				(0.030)	(0.113)
Employment Type: Temp. Contract				-0.047*	0.062*
				(0.028)	(0.032)
Employment Type: Entrepreneur				0.205***	-0.166***
				(0.019)	(0.012)
Employment Type: Other				-0.935***	-0.489***
				(0.089)	(0.083)
Firm Size: 10-50					0.234***
					(0.005)
Firm Size: 50-250					0.445***
					(0.008)
Firm Size: 250+					0.620***
					(0.014)
Firm Industry: Mining					0.326***
					(0.055)
Firm Industry: Manufacturing					0.060***
					(0.016)
Firm Industry: Electricity, water, waste					0.187***
					(0.027)
Firm Industry: Construction					0.007
					(0.016)
Firm Industry: Trade					-0.022
					(0.017)
Firm Industry: Hotel					-0.148***
					(0.019)
Firm Industry: Transport, post					0.026
					(0.033)
Firm Industry: Finance					0.382***
					(0.052)
Firm Industry: Real estate					-0.035*
					(0.019)
Firm Industry: IT, RD					0.110***
					(0.028)
Firm Industry: Public: govt, health, educ					-0.057***
					(0.022)
Firm Industry: Other					-0.041**
					(0.018)
Firm Revenue (Real, HUF)					0.000***
					(0.000)
Firm Value Added (Real, HUF)					0.000***
					(0.000)
Firm K/L ratio					0.000***
					(0.000)
Observations	6,743,271	6,743,271	4,047,689	4,007,438	2,749,744
R-squared	0.052	0.143	0.021	0.252	0.401
Fixed Effects	Year	Year	Year	Year	Year
Cluster	-	-	Firm	Firm	Firm
Number of Convicts	7012	7012	7012	7012	7012
Number of Non-Convicts	64348	64348	64348	64348	64348
Abs. Diff.: After-Before	.031	.035	.164	.066	.027
After = Before F-test 2-sided p	.000	.000	.000	.000	.021
After >Before F-test 1-sided p	.000	.000	.000	.000	.010

Robust standard errors are used in estimations (1) and (2). Clustered standard errors in estimations (3)-(6): firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The model is estimated on the time-frame 2004-2011. The matching is based on an k-nearest matching (with 10 neighbours) on the common support, with no replacement and ties.
Baselines for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode
Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture

Table 39: VII. Matched Control Group - 1 Year - Kernel

VARIABLES	(1) Employed	(2) Employed	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)
Convict & Before Prison	-0.178***	-0.156***	-0.083***	-0.045***	-0.061***
	(0.001)	(0.001)	(0.021)	(0.016)	(0.016)
Convict & After Prison	-0.201***	-0.182***	-0.138***	-0.109***	-0.109***
	(0.002)	(0.002)	(0.025)	(0.021)	(0.020)
Prison Spell Length (Month)	0.000***	0.000***	-0.001	-0.002**	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Number of Prison Spells	-0.073***	-0.070***	-0.066***	-0.048***	-0.041***
	(0.001)	(0.001)	(0.014)	(0.012)	(0.013)
Age	0.081***	0.076***	0.034***	0.025***	0.028***
	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
Age Squared	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.033***	0.027***	0.073***	0.217***	0.243***
	(0.000)	(0.000)	(0.013)	(0.007)	(0.006)
Ln(Real Health Expenditure)		0.013***		-0.001***	-0.004***
		(0.000)		(0.000)	(0.000)
Receives Care Allowance		-0.588***		-0.482***	-0.406***
		(0.000)		(0.008)	(0.010)
Receives Disability Pension		-0.453***		-0.406***	-0.408***
		(0.000)		(0.008)	(0.020)
Education: some technical (max. low-skilled blue)		0.137***		0.052***	0.076***
		(0.000)		(0.013)	(0.012)
Education: technical school (max. skilled blue)		0.107***		0.034***	0.043***
		(0.000)		(0.007)	(0.007)
Education: some tertiary (max. white/professional)		0.183***		0.063***	0.095***
		(0.000)		(0.010)	(0.016)
Education: tertiary (max. manager top/other)		0.198***		0.118***	0.168***
		(0.000)		(0.009)	(0.008)
Education: unknown (entrepreneur)		0.109***		-0.054***	0.033***
		(0.000)		(0.008)	(0.008)
Regional Unemp Rate					
		(0.001)		(0.181)	(0.126)
Roma 5-10% zipcode		-0.026***		-0.038***	-0.049***
		(0.000)		(0.007)	(0.006)
Roma 10%+ zipcode		-0.053***		-0.051***	-0.068***
		(0.000)		(0.008)	(0.009)
Tenure on Job (Month)				0.003***	0.003***
				(0.000)	(0.000)
Occupation: Other manager				0.045***	-0.005
				(0.015)	(0.011)
Occupation: Professional				0.128***	0.189***
				(0.031)	(0.016)
Occupation: White Collar				-0.266***	-0.265***
				(0.019)	(0.010)
Occupation: Skilled Blue Collar				-0.635***	-0.589***
				(0.020)	(0.009)
Occupation: Low-Skilled Blue				-0.500***	-0.590***
				(0.022)	(0.014)
Occupation: Unskilled				-0.815***	-0.802***
				(0.021)	(0.009)
Occupation: Unknown:entrepreneur				0.022	0.036***
				(0.016)	(0.014)

Robust standard errors are used in estimations (1) and (2). Clustered standard errors in estimations (3)-(6): firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The model is estimated on the time-frame 2004-2011. The matching is based on a kernel matching on the common support, with caliper(0.01).

VARIABLES	(1) Employed	(2) Employed	(3) Ln(Daily RWage)	(4) Ln(Daily RWage)	(5) Ln(Daily RWage)
Employment Type: Public Sector				-0.140***	-0.453***
				(0.022)	(0.056)
Employment Type: Public Work Program				-0.931***	-0.350***
				(0.029)	(0.107)
Employment Type: Temp. Contract				-0.320***	-0.036**
				(0.025)	(0.016)
Employment Type: Entrepreneur				-0.206***	-0.146***
				(0.025)	(0.008)
Employment Type: Other				-0.302***	-0.046***
				(0.020)	(0.016)
Firm Size: 10-50					0.274***
					(0.003)
Firm Size: 50-250					0.499***
					(0.007)
Firm Size: 250+					0.652***
					(0.015)
Firm Industry: Mining					0.344***
					(0.045)
Firm Industry: Manufacturing					0.101***
					(0.012)
Firm Industry: Electricity, water, waste					0.253***
					(0.032)
Firm Industry: Construction					0.021*
					(0.012)
Firm Industry: Trade					0.021
					(0.015)
Firm Industry: Hotel					-0.082***
					(0.016)
Firm Industry: Transport, post					0.055
					(0.049)
Firm Industry: Finance					0.401***
					(0.044)
Firm Industry: Real estate					0.018
					(0.013)
Firm Industry: IT, RD					0.200***
					(0.024)
Firm Industry: Public: govt, health, educ					0.020
					(0.014)
Firm Industry: Other					0.029**
					(0.013)
Firm Industry: Small enterprise					-0.011
					(0.016)
Firm Revenue (Real, HUF)					0.000**
					(0.000)
Firm Value Added (Real, HUF)					0.000**
					(0.000)
Firm K/L ratio					0.000***
					(0.000)
Observations	179,930,535	179,930,535	129,004,816	128,049,165	79,349,617
R-squared	0.101	0.216	0.014	0.337	0.437
Fixed Effects	Year	Year	Year	Year	Year
Number of Convicts	7012	7012	7012	7012	7012
Number of Non-Convicts	1,868,382	1,868,382	1,868,382	1,868,382	1,868,382
Abs. Diff.: After-Before	.023	.026	.055	0.064	.048
After = Before F-test 2-sided p	.000	.000	.000	.000	.000
After >Before F-test 1-sided p	.000	.000	.000	.000	.000

Robust standard errors are used in estimations (1) and (2). Clustered standard errors in estimations (3)-(6): firm ID. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The model is estimated on the time-frame 2004-2011. The matching is based on a kernel matching on the common support, with caliper(0.01).
Baselines for categorical controls are: Female, Education: Unskilled, no schooling, 0-5% Roma Population lives on given zipcode
Occupation: Top Manager, Employment Type: Regular Employment Contract, Firm Size: 0-10, Firm Industry: Agriculture