Searching for informal work using administrative data *

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Abstract

This paper investigates informality in Italy driven by the intense use of non-standard jobs. In the first part, using administrative data released by the Italian Social Security Institute combined with data of firms' financial statements and inspections data, I construct an irregular job rate implementing machine-learning technique. My micro-economic irregular job rate is consistent with irregular job rate provided by the Italian Institute of Statistics. Temporary and part-time contracts are highly correlated with known measures of undeclared work. In the second part, I show with an event study analysis that lower EPL induce firms to more easily fire irregular workers. Finally, I also investigate how less financial development positively impact the number of irregular part-time workers, especially in Services and Commerce.

JEL Classification Numbers: H26, H29.

Keywords: flexible jobs, part-time, informality, prediction.

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1 Introduction

The dilemma of shadow labour in politics as in economics is largely debated and still ongoing. When the cost of hiring someone "officially" increases (a large burden of taxation and social security contributions on wages), agents' response is to choose the cheaper alternative, the "unofficial" labour market (Feld and Schneider, 2010). Flexible jobs (or non-standard jobs) are born with the objective of being a deterrent for irregular workers, thanks to a more efficient and less strenuous regulation. Equally, these contracts can have the perverse effect of being an incentive for informality. Informality arises when workers are employed in "semi-illegal" irregular jobs, referring to social security contributions, or employment status, or employment contract. As documented by Bonnet et al. (2019), informality concerns 70% of all employment in developing and emerging countries, and about 18% in developed countries, with temporary and part-time contracts significantly more likely to be informal compared with permanent full-time.[1] Italy, as one of the European countries with the greatest amount of undeclared workers,[2] in order to improve regular hires, has strongly encouraged the use of flexible jobs, through many changes of labour legislation, with a dynamic of the labour market towards contracts not long-lasting and an intense use of part-time, instead of full-time.[3] In a context in which firms tend to seek refuge behind under-declaring workers, in order to save on labour costs, and a growing tendency to non-standard jobs, one question could be: "Are firms with an excessive prevalence of non-standard jobs involved in informality?".

This paper aims to construct an irregular job rate in order to investigate the irregularity behind non-standard contracts, the so called "grey labour", using administrative data at micro level from the Italian Social Security Institute (*Istituto Nazionale di Previdenza Sociale* hereafter, INPS), with an empirical approach which is made up of two parts.

The first part is devoted to construct the irregular job rate combining firms' employment information by month-year (years selected are 2012-2015), with data of firms' financial statements provided by CERVED data (for non-agricultural firms), and processed taking advantage from machine-learning techniques.[4] I use LASSO (Least Ab-

[1]Schneider and Enste (2000) calculate that informal sector accounts for 10 to 20 percent of GDP in most OECD countries, 20% to 30% in Southern European OECD countries and in Central European transition economies. For a comprehensive review of all the possible characteristics of informality across countries see Hazans (2011).

[2]The Italian National Institute of Statistics (Istat) calculates that the value added of the shadow or underground economy is worth about 12,1% (211 billion) of the Italian GDP. Moreover, between all the components of the underground economy, the impact of under declaration and irregular job is higher with respect to the unlawful activities, respectively evaluated 176 billion and 19 billion in 2017

[3]INPS (2019) documents that in 2018 *part-year* employees, both *part-time* and *full-time*, and *full-year part-time* contracts have grown, while *full-year full-time* contracts have slowly decreased. In 2018, *part-year* employees have increased, both *part-time* (+5,8%) and *full-time* (+4,5%).

[4]Economic literature has found numerous and different ways to take advantage of machine-learning

solute Shrinkage And Selection, Tibshirani (1996)) to generate firm specific prediction models for the share of non-standard workers. Based on the model selection, I predict the share of non-standard workers. I define as "irregular" firms the ones for which the real value falls above the upper limit of the confidence interval of the predicted value. Each time the real value is higher than the upper limit, that value is considered as irregular. Namely, if the real value provided by a firm is 100 and the upper limit of the confidence interval of the predicted value is 50, then that real value is considered as irregular. In this way, it is possible for me do define a "score of irregularity". Scores range from 0 to 100%. A score at 100% means that for each month-year available, that firm is observed irregular: it has a greater tendency to anomalies.

Once defined the irregular job rate, I check its reliability comparing it with other measures of irregular job provided by the Italian Institute of Statistics (hereafter, Istat). My micro-economic indicator of irregular job is consistent with the Istat indicator of irregular job. Correlation is positive, equal to more than 90% (in terms of R2) and statistically significant for irregular part-time contracts, temporary part-time contracts (0.8998) and permanent part-time contracts (0.9454), while for full-time contracts correlation is negative and not statistically significant. Southern regions have the highest values of irregularity, such as Campania and Calabria, while the lowest values are concentrated in Northen regions (such as Valle d'Aosta and Trentino Alto Adige).

I also provide a descriptive analysis of irregular units looking at type of contracts, inspections and credit constraint measure. Irregular firms employee less full-time contracts in favour of part-time, with a percentage of part-time for these contracts not greater than the 40%. Moreover, they have, compared with regular firms, a significant higher percentage of part-time females workers than part-time males, the highest value employed in Services. Firms located in Centre and South of Italy have highest values of irregular part-time contracts with respect to North regions. In South and Islands part-time males are in mean more than females and particularly high with respect to part-time male in North and Centre of Italy. In terms of credit constraint, looking at SA index (Hadlock and Pierce, 2010), irregular firms reach higher maximum values of the SA index, compared

prediction capacity. Focused on pure *prediction*, its main goal is to find functions that work well *out-of-sample*. The powerful techniques used in machine-learning may be useful for developing better estimates of the counterfactual, potentially improving causal inference (Varian, 2016). In addition to the most common tools developed by researchers, machine-learning has the ability to discover complex structure not specified in advance, manages to fit complex and very flexible functional forms to the data without simply over fitting, finds functions that work well *out-of-sample* (Mullainathan and Spiess, 2017). Machine-learning can: manage unconventional data as satellites images, online posts, reviews or comments provided by people (Henderson et al. (2012); Blumenstock et al. (2015); Glaeser et al. (2018); Kang et al. (2013); Antweiler and Frank (2004)); solve estimation problems (Belloni et al. (2012); Carrasco (2012); Belloni et al. (2016); Chernozhukov et al. (2018); Athey and Imbens (2016)); improve the impact of a policy, predicting who is more likely to belong to groups with a higher payoff and groups where the effect may be zero (Kleinberg et al. (2015); Andini et al. (2018)).

with regular firms, meaning that irregular firms face a higher probability of difficulties of access to credit than the regular ones. Thanks to INPS inspections data, I can also check the reliability of my definition of irregular firms if these firms have received at least one inspection. Irregular firms cover about 25% of inspected firms between years 2012-2015.

In the second part of the paper, I combine results provided in the first part to investigate if these non-standard contracts are effectively used to hide work that otherwise would be completely undeclared. First, I use a quasi-experimental setting to exploit the causal impact on irregular firms of a less stringent employment protection legislation (hereafter, EPL). An increase in EPL may create incentives for firms to hire (and possibly fire) workers in the informal sector where labour adjustment costs are lower (Di Porto et al., 2016). I take advantage from the Italian reform of 2015, the "Jobs Act", which eliminates any possibility that the worker unfairly fired could be reintegrated and firms only have to pay a reimbursement to workers, making in this way labour adjustment costs lower. Restricting the time-frame to the year 2015, I rely on a Difference-in-Differences approach at monthly level, before and after March 2015, for irregular firms who hide undeclared work using non-standard contracts and those who do not. I look at 5 different outcomes measured at monthly for each irregular firm i: total number of part-time, temporary part-time, permanent part-time, part-time workers (female), part-time workers (male). Results show that for the economic sector code Commerce the total number of irregular part-time contracts, after the "Jobs Act" implementation, decreases. Namely, the reform implementation leads to a decrease in part-time contracts for irregular firms in months m compared to March, when the effect is normalized to 0. In April the average effect is around -0.0082; in May -0.0102; in June -0.0115 until December in which the effect is -0.0157. In addition, when I consider irregular firms with the highest score of irregularity (100%), after the policy implementation, the number of irregular temporary part-time contracts in Services decreases; in April the average effect is around -0.0083; in May -0.010; in June -0.0129 until December in which the effect is -0.0230.

Second, I combine results provided in the first part of the paper, where I identify irregular firms with my micro-based score of irregularity, to explore the link between financial development and shadow labour, in the spirit of Capasso and Jappelli (2013). I regress irregular contracts on the indicator of local financial development, provided by Istat, which measures the risk of financing for the Italian Provinces. This indicator measures the rate of bad credits for firms and households located in each Italian Province, giving a measures of risk credit. Given the construction of this index, higher the index is, higher the risk credit in that Province. Results show that a higher index of bad credits positively impacts the number of irregular part time contracts (female) in Services (coefficient is 0.0098). I control for the level of GDP per-capita and unemployment rate.

Moreover, if I look at irregular firms defined with a score of irregularity of 100%, the positive impact of bad credits on irregular part-time contracts (female) (coefficient is around 0.014).

Being an heavy burden for the economy, many policy interventions have the objective of fighting tax evasion and informal (illegal) employment. A critical aspect of shadow economy is the lack information. Being able to identify the potential irregularity hidden behind a regular contract observed can significantly improve the fight against irregular jobs. In this paper I show that, combining different sources of data and methods, it is possible to characterize potential irregular units, making in this way also inspection procedure more efficient. Indeed, how optimally allocate inspectors is a decision problem, and knowing which establishment or individual is more likely to have violations would be equivalent to knowing which ones should be inspected (Glaeser et al., 2016).[5] Italy represents a good and interesting setting, due to the highest levels of evasion and underground work, and the numerous interventions against shadow economy implemented by Governments. My results contribute to document how underground activity is impacted by labour regulations and it is correlated with the level of financial development and credit access. More specific, I show that irregular workers are covered by non-standard jobs, with a focus on part-time solutions and female workers.

The reminder of the paper is organised as follows. Section 2 describes data; Section 3 discusses methodology for the definition of irregular firms; Section 4 presents correlation with Istat data; Section 5 analysis the impact of lower EPL on irregular workers; Section 6 investigates the role of financial development on shadow labour. Finally, Section 7 concludes.

2 Data

I use different sources of data in order to get the dataset and variables used for the analysis.

Matched employer-employee records: I consider the universe of non-agricultural firms for which they are reported detailed information about employees covered by Social Security, filling the *Uniemens* modules. I use monthly data for years 2012-2015. Firms are identified by a unique Tax Identification Number (TIN) and associated to a Contribution Identification Number. For each worker-firm record, information available is: type of contract (permanent, temporary or seasonal; part-time or full-time), beginning and end

[5] Glaeser et al. (2016) use prediction tournaments to improve city operations. Comparing algorithms' performance *out-of-sample*, authors show that using the winning ones increases significantly inspections efficacy, better identifying restaurants to inspect in Boston. Estimates show a 30% to 50% improvement in the number of violations found per inspection.

date of the contract, alongside the underlying motivation (e.g. layoff, quit), wage, broad occupation group. I only select firms in activity for years considered, dropping out all the others. Data are collapsed in order to have the monthly number of employees for each firm for all the years considered, with detailed information about the type of contract. To be specific, I construct the following variables: total number of employees, the total number of temporary, permanent, and seasonal workers. In addition, for each type of contract I also distinguish if they are part-time or full-time, males or females. Moreover, for part-time contracts, I have the possibility to look at the percentage of part-time, that is the exact measure of part-time for each contract (50%, 80%, 90%,...) and the distinction between if part-time contracts are: horizontal (subject works less hours all the week), vertical (subject works less day of the week full time) and mixed (a mix of horizontal and vertical).[6] Thanks to all these information, it is possible for me to identify employees for their exact type of contract.

CERVED data: using TIN, I match worker-firm record with CERVED data. In this way, I have for each firm the exact information about employees and financial statements. I consider the sample period of 2012-2015.[7]

Inspections data: thanks to the INPS archive, I can use data of inspections for the years 2002-2014. For each inspected firm, it is reported: beginning and end date of the inspection, the number of inspection for each year for each firm (it is possible for a single firm to receive more than one inspection), the result of the inspection (black workers or not, total omissions in workers' contracts). The 2014 is the last year available for INPS archive, because in 2015, with the Jobs Act, there is the birth of a new agency, the INL (Ispettorato Nazionale del Lavoro).[8]

ISTAT data: index of Italian irregular employees by economic sector codes and regions for period 2005-2017, based on the Labour Force Survey. I compare my irregular units, defined using INPS data, with the irregular job rate computed by Istat. It is used the rate of undeclared work, as the % of units of undeclared work over total units of work. Istat defines as ULA (Units of full-time work) all the labour units, for all the job positions covered by employed. ULA are computed as the share of total number of worked hours over the average number of worked hours full-time. The irregular ULA are defined as all

[6]Until 2015, employers must use different part-time contracts for the three different possibilities. After 2015 Jobs Acts, employers do not have to use different contracts for different part-time. Part-time contract is only one, and they must specify in the contract number of hours or days, or both of the part-time.

[7]Values of the variable Roe are winsorized if it is less than 20 and greater than 100. Values of the variable Roa are winsorized if it is less than 20 and greater than 30.

[8]Before the reform of 2015, the inspection activity was carried out by three different subjects: Ministero (labour regulation), INPS (social security) and INAIL (job security). In order to simplify procedures and coordinate the activity of the three subjects, in 2015 it was approved the creation of the new agency, the INL.

the work units without regulation, and so that not directly observed.

3 Definition of irregular firms

The rich INPS archive gives me the possibility to construct different outcomes of interest, based on the different and possible types of non-standard contracts: temporary, part-time, open-ended part-time, temporary part-time and temporary full-time contracts. I compute the ratio of each of these contracts with the total of employees. All the ratios computed are monthly, defined for each firm in years 2012-2015.[9] These ratios are my main outcome variables for the first step of my approach in order to define irregular firms which consists of computing the predicted values of these different ratios.

3.1 LASSO method

For prediction I take advantage from LASSO method (Tibshirani, 1996) to select the model with the best prediction of my outcome variable of interest. Combining INPS and CERVED data, I have for each firm complete information about employees and financial statements. I use LASSO to compute the best prediction of my outcomes. This methodology is particularly well suited for outcomes prediction because it works as a covariate-selection method, excluding covariates whose estimated coefficients are zero and including only covariates whose estimates are not zero. It is part of the "Shrinkage Methods", which minimize RSS (residual sum of squares) with a penalty for model size. LASSO does the *model selection*, choosing the one with the best performance *out-of-sample*. The model selected is suitable for making prediction in samples outside the one it is used fro the estimation.[10] For the prediction, I include in the LASSO model all the

[9]For computation of the predicted value I will use the logarithm + 1, in order to consider only positive values of the outcome variables of interest.

[10]LASSO finds solution for the following general problem:

$$y_i = \beta_0 + \beta_1 x_{1,i} + ... + \beta_p x_{p,i} + \epsilon_i \tag{1}$$

by minimizing the prediction error subject to the constraint so that the model is not too complex (sparse). LASSO measures complexity by the sum of the absolute values of $\beta_1, \beta_2, ..., \beta_p$, minimizing the following formula:

$$\frac{1}{2N}(y - X\beta')'(y - X\beta') + \lambda \sum_{j=1}^{p} |\beta_j| \tag{2}$$

the first term $(y - X\beta')'(y - X\beta')$ is the in-sample prediction error; the second term $\lambda \sum_{j=1}^{p} |\beta_j|$ is a penalty that increases in value the more complex the model is. LASSO shrinks parameter estimates towards zero, and the extent of shrinkage is determined by the *tuning parameter* λ. LASSO minimizes equation 2 for given values of λ, then it chooses one of those solutions as best based on another criterion, such as an estimate of the *out-of-sample* prediction error. It provides various ways of selecting λ: CV, financial statements variables, industry codes at two digits, geographic location (regions), age of firms (defined as group of age).

3.2 Score of irregularity

Once computed the predicted values, the second step is the definition of irregular firm. Computing the confidence interval of the prediction, I discriminate between statistical error and another type of error which should be associated with an informal situation. I define as informal units the ones for which the real value falls above the upper limit of the confidence interval of the predicted value. Each time the real value is higher than the upper limit, that value is considered as irregular. In this way, I select "irregular" firms. The score of irregularity defines an "intensity". I check the number of times a firm has an irregular value, for each month-year, with a score range that goes from 0 to 100%. Namely, a firm with a 100% score of irregularity means that this firm has irregular values 12/12 months in a year.

4 Correlation with ISTAT data

My irregular score of irregularity is consistent with the macroeconomic indicator of irregular job provided by Istat, based on Labour Force Survey. Istat irregular job rate is computed as percentage of irregular ULA over the total number of ULA. It is yearly, at regional level, and economic sector codes are grouped in 4 macro-categories: Agriculture, Mining, Construction, and Services.[11]

I present correlations between Istat irregular job rate and INPS irregular contracts defined using my score of irregularity.[12] I check correlations for the different types of irregular contracts I observe in INPS data. Namely I use: total of part-time, temporary part-time, permanent part-time, temporary full-time.

First, I consider correlation with irregular part-time contracts and Istat irregular job rate. Correlation is positive and statistically significant (0.9489), see Table 1. Figure 1 plots the regional averages of the irregular part-time contracts against the index of irregularity provided by Istat. Southern regions have the highest values of irregularity, such as Campania and Calabria, while the lowest values are concentrated in Northen regions.

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adaptive lasso, and a plugin estimator.

[11] Agricultural firms are dropped from my analytic sample.

[12] I compute Pearson correlation coefficient, which ranges from -1 to 1. Closer to 1 means strong correlation. A negative value indicates an inverse relationship (roughly, when one goes up the other goes down).

The second correlation is for irregular temporary part-time contracts and Istat irregular job rate. Correlation is positive and statistically significant (0.8998), see Table 2. Again Southern regions have the highest values of irregularity and average values of irregular contracts (Figure 2). While for irregular temporary part-time contracts correlation is positive, the opposite happens for irregular temporary full-time contracts. In this case correlation with Istat irregular job rate is negative and not statistically significant (-0.4214), see Table 3.

The last correlation is with irregular permanent part-time contracts. As for temporary part-time contracts, also in this case correlation with Istat irregular job rate is positive and statistically significant (0.9454), see Table 4. Again Southern regions have the highest values of irregularity, specifically Campania, Calabria and Sicilia which are in Italy commonly known as regions with the higher propensity of irregular work (see Figure 3).

5 Descriptive analysis

5.1 Part-time contracts

Focusing the attention on a part-time solution associated to a temporary or a permanent contract, considering the relationship between the share of part-time and employee related expenditure at firm level, it can be argued if firms use part-time workers with a higher share of full-time with respect to the average. Put differently, a 90% part-time worker generates higher expenditure with respect to an average 50% part-time. I check for part-time contracts the amount of part-time (50%, 80%, 90%...). Figure 4 shows mean of part-time contracts looking at the percentage of part-time, comparing the group of regular and irregular firms. Regular firms employee in mean more full-time contracts (21.38%) with respect to irregular firms where the percentage is around 16.37. Values of full time contracts for both categories are not particularly different, however irregular firms employee less full-time contracts in favour of part-time contracts, with a percentage of part-time for these contracts not greater than the 40%. These evidence could reflect the fact that irregular firms take advantage from part-time contracts to hide full-time workers. In this sense, the propensity to have in mean part-time contracts with a percentage of part-time which is not to much high is in line with the hypotheses of informality: they are declared as a 50% part-time, saving on contributions, but workers schedule is higher.

It is well known that the use of part-time contracts is mostly reserved to women workers. Non-regular labour positions are often covered by women employees. Figure 5 compares part-time workers for regular and irregular firms, distinguished for male and female part-time. Clearly, based on my definition of irregular firms, part-time contracts for this category are higher than regular, but if we look at the comparison between males and females, it is clear that regular firms have in mean the same percentage of part-time female and male, while for irregular firms a significant higher percentage of part-time is given by female workers.

Table 5 reports mean and standard deviation for the different types of part-time, for four macro-categories of economic sector codes: Manufacturing, Services, Constructions and Commerce. Commerce employees more horizontal part-time with Services. The lowest values in mean are in general for mixed part-time. In general, for all the economic sector codes, irregular firms prefer the horizontal part-time formula and females. Females part-time are more employed, with the highest value in Services. Table 6 referees to these type of contracts looking at the geographic location of firms. Firms located in Centre and South of Italy have highest values of irregular part-time contracts with respect to North regions. In South and Islands part-time males are in mean more than females and particularly high with respect to part-time male in North and Centre of Italy.

5.2 Credit constraint

A not reliable financial statement, impaired loans or difficulties to have access to credit market, could represent an important drivers for firms to push firms to save on costs in irregular ways. For these reasons, I check the reliability of my results, looking at credit constraint for irregular firms. For credit constraint I use the SA index, derived by Hadlock and Pierce (2010). The index is computed in the following way:

$$SAindex = -0.737 \times SIZE + 0.043 \times SIZE2 - 0.040 \times AGE \tag{3}$$

where $SIZE$ is the natural logarithm of inflation adjusted total assets; AGE is defined as the number of years of the firm (since it is born or listed). Higher is the index and higher is the probability for a firm to face financial constraints. Irregular firms in mean have the same value of the index as the regular firms, but they reach higher maximum values of the SA index, compared with regular firms. This could reflect the case of some irregular firms with strongly difficulties to access to credit, based on some financial statements information (see Table 8).

5.3 INPS Inspections

INPS inspections advocate to control for all the contracts for which it is compulsory the payments of social security contributions. Inspectors of "Social Security" have the power to ensure the compliance of the social security legislation. These inspectors have access to workplaces, examine firms, compulsory books, acquire declarations of workers and employers, and they can start a caution in case of irregularities found during inspections. A labour inspection visit can be generated from the three different situations: 1) **request of intervention:** it is a complaint against a specific employer, reported from one or more workers, regarding unlawful or irregular treatment received by workers during their working activities; 2) **the office communication:** consisting of transmission by another administrative institute or by the judicial police; 3) **the autonomous initiative:** such as the planned labour inspection visit. According to a specific planning or operational guidelines, it is decided to inspect a specific firm. This last situation can take place also based on statistics studies and monitoring activities carried out previously by territorial supervisory agencies. The **autonomous initiative** better reflects the essence of labour inspections, thanks to the "*surprise effect*" that provides a higher effectiveness of the investigation.[13]

The method I propose in order to define irregular firms is in line with this third method. Inspections can be planned according to the score of irregularity assigned to firms. Based on a precise analysis, the inspection activity is not driven by initiative from workers or entrepreneurs. The "*surprise effect*", which provides a higher effectiveness of the investigation, is preserved and it is to be hoped that the inspection activity will be more precise.

For inspections, data reports the date of the beginning and the date of the end of the inspection, the identification code of the inspected firm and the type of irregularity discovered (black worker, all omitted, some omitted). During years, inspection activity has been reduced, as shown in Figure 6. Less firms inspected, less irregularities are discovered. This means that firms during years have faced a lower probability of being inspected, so irregular firms should have more incentive to not comply. Table 9 reports descriptive statistics of total of omissions for irregular firms inspected, by different economic sector codes: in mean the highest number of omissions for irregular firms is in Services (28,959).

I merge my informal data with inspections data, in order to check whether firms I define as irregular, have also received an inspection by INPS, having in this way an additional information about firms reliability. I check for the number of irregular firms which have received at least one inspection by INPS during years available 2012-2015. Irregular firms cover about 25% of inspected firms during the years considered (see Table 10).

[13]For a more developed discussion about labour inspection in Italy see Fasani (2011).

6 Employment protection legislation and informality

In the first part of the analysis, I show that non-standard jobs, temporary and part-time, are correlated with irregular work. This section aims to develop the second part of the analysis where I investigate if these contracts are effectively used to hide work that otherwise would be completely undeclared. In order to evaluate this possibility, I combine results provided in the first part, where I have a distinction between regular and irregular contracts, with lower EPL. Indeed, the decision of firms between formal or informal sector depends on the trade-off between costs associated to regular and irregular employment. As in presence of a high level of hiring costs, also firing costs may induce firms to find resort in informal labour market, in order to have more flexibility in their employment decisions. A strand of literature argues that rigid/high EPL reduces firms' ability to adjust their levels of employment and drives to informal sector to avoid tax burdens. Cappellari et al. (2012) point out that changes in EPL for temporary employment produces substitution between different types of temporary contracts while leaving total employment unchanged. Hijzen et al. (2017) show that strict EPL produces substitution between permanent contracts and temporary contracts with the perverse effect of reducing rather than increasing worker security on average. An increase in EPL may create incentives for firms to hire (and possibly fire) workers in the informal sector where labour adjustment costs are lower (Di Porto et al., 2016).

I investigate the impact of a more flexible EPL, meaning a higher ability for firms to fire workers, on informal contracts defined in the previous part of the analysis. In March 2015, the Italian Reform "Jobs Act" eliminates any possibility that the worker unfairly fired could be reintegrated and firms only have to pay a reimbursement to workers. In addition to what already defined by Fornero Reform (2012), the Jobs Act makes firing someone easier for firms.[14]

Restricting the time-frame to the year 2015, I rely on a Difference-in-Differences approach at monthly level, before and after March 2015, for irregular firms who hide undeclared work using non-standard contracts and those who do not. In order to assess the direct impact of the 2015 reform the identification leverages the variation of irregular non-standard contracts for irregular firms. To test for the parallel trend assumption,

[14] The Fornero Reform (2012) changes some of the rules related to the conclusion of the employment relationship. According to Italian Law an individual dismissal is legal only when it is justified by cause, or subjective reasons, related to the part of the worker. There is the possibility for the worker to appeal the firing decision. If the dismissal is declared unfair, firms must pay a compensation. The maximum compensation varies with the firm size. In 1990 Italy introduced a labour market reform which increased EPL for permanent workers in firms with less than 15 employees relative to those in firms with more than 15 employees. In 1970, the Statuto dei Lavoratori (Law No. 300) established that all firms with more than 15 employees reintegrate workers and pay their foregone wages in case of unfair dismissals. This rule is not applied for firms with less than 15 employees.

I estimate differences for all the 12 months of the year 2015, with March as reference month in which the policy becomes effective and the effect is normalised to zero. I look at 5 different outcomes measured at monthly for each irregular firm i: total number of part-time, temporary part-time, permanent part-time, part-time workers (female), part-time workers (male). I control for fixed effects at firm level, to capture time-invariant heterogeneity across firms, months fixed effects. Standard errors are clustered at firm level to avoid potential serial correlation across periods Bertrand et al. (2004).

The estimated equation reads as follows:

$$Y_{i,m} = \sum_{k=1}^{12} \beta_k^T \mathbb{1}(k = m) \times T_i + \lambda_m + \lambda_i + \epsilon_{i,m} \tag{4}$$

$Y_{i,m}$ is the outcome variable for firm i at month m, λ_m captures month fixed effects, λ_i is firm fixed effects, β_k is the coefficient of interest in month k. Results are shown in appendix A and do not provide any significant evidence of the Jobs Act reform to irregular firms in terms of informal non-standard contracts.

As second approach, I estimate a modified version of equation 4 in which I consider irregular firms for four different economic sector codes. I look at irregular firms in: Manufacturing, Construction, Commerce and Services. The new estimated equation is:

$$Y_{i,m,s} = \sum_{k=1}^{12} \beta_k^T \mathbb{1}(k = m) \times T_i + \lambda_m + \lambda_i + \epsilon_{i,s,m} \tag{5}$$

Figure 7 shows results for the economic sector code Commerce. The difference in total number of part-time contracts is fairly flat in the two months before the reform and starts to immediately go down after March. In line with what suggested by previous literature, when the cost of firing decreases, firms who employee irregular workers fire informal workers. The total number of irregular part-time contracts, after the Jobs Act implementation, decreases. Namely, the reform implementation leads to a decrease in part-time contracts for irregular firms in months m compared to March, when the effect is normalized to 0. In April the average effect is around -0.0082; in May -0.0102; in June -0.0115 until December in which the effect is -0.0157 (see Table 11). Pre-trends provide suggestive evidence of the exogeneity of the policy. After the policy, when the labour adjustment costs are lower, the number of irregular part-time decreases. For the other outcomes of interest in Commerce and the other economic sector codes, results are not statistically significant (see Appendix B).

As third approach, I estimate another modified version of equation 4 in which I consider irregular firms for different economic sector codes if the score of irregularity is 100%. The new estimated equation reads as follows:

$$Y^{100}_{i,m,s} = \sum_{k=1}^{12} \beta^T_k \mathbb{1}(k=m) \times T_i + \lambda_i + \epsilon_{i,s,m} \quad (6)$$

Figure 8 shows that the difference in total of temporary part-time is flat in the two months before the reform, and after March these contracts for firms with a score of irregularity of 100% in Services decreases. In April the average effect is around -0.0083; in May -0.010; in June -0.0129 until December in which the effect is -0.0230 (see Table 12). For the other outcomes and economic sector codes (see Appendix C).

7 Financial development

In this section, as in section 6, I combine results from the first part of analysis to investigate the impact of another channel considered by literature as a determinant for irregular work: the level of financial development. I explore the link between financial development and informality for the irregular units I identify with my micro-based score of irregularity. A strand of literature emphasises the role of financial development as an element of public institutions linked to underground economy. Higher cost of credit represents an important opportunity cost of working in the shadow. Financial constraints tend to induce informality, especially for small firms or firms located in small cities (Dabla-Norris et al., 2008). Beck et al. (2014) find that the underground economy is negatively associated with the availability of private credit and individuals' subjective assessment of their access to credit. Capasso and Jappelli (2013) provide a theoretical and empirical study of the relation between financial development and the size of the underground economy, showing that financial development (a reduction in the cost of external finance) can reduce tax evasion and the size of the underground economy.

I construct my empirical strategy in the spirit of Capasso and Jappelli (2013). In their paper, authors regress their index of irregularity on an index of financial development and a series of control variables at regional level. Based on their approach, I regress irregular contracts on the indicator of local financial development, provided by Istat, which measures the risk of financing for the Italian Provinces. This indicator measures the rate of bad credits for firms and households located in each Italian Province, giving a measures of risk credit. Given the construction of this index, higher the index is, higher is the risk credit in that Province. If in a Province the index is high, the impact on the number of irregular contracts is expected to be positive. Put differently, difficulties in credits access, meaning a less financial development in that Province, translate in a higher number of irregular contracts as a result of firms' choice of working in the shadow. I consider five different outcomes, given the types of irregular contracts: part-time, temporary part-time, part-time (female), part-time (male) and permanent part-time. In the previous section, I show that the impact of lower EPL on irregular contracts is significant when the definition of irregular firms takes into account also the economic sector code. For evaluating the impact of financial development, I consider irregular contracts also considering the economic sector codes: Manufacturing, Construction, Services and Commerce.

I estimate the following equation:

$$U_{i,s,p} = \beta_1 FD_p + X_{p,t}\delta + X_i\zeta + \mu_i + \gamma_t + \epsilon_{i,s,p} \tag{7}$$

where U is an indicator of irregular contracts for irregular firm i in sector s in Province p. FD is the Istat index of financial development for Province p; $X_{p,t}$ is a set of controls; μ_i sector fixed effects, γ_t time fixed effects and ϵ the error term. Standard errors adjusted for clustering at the provincial level. The main coefficient of interest is the index of local financial development. In Table 13 results show that a higher index of bad credits positively impacts the number of irregular part time contracts (female) in Services (coefficient is 0.0098). I control for the level of GDP per-capita, unemployment rate and age of firms. In addition, since South of Italy tends to be be the least financially developed and more prone to shadow labour, I add as control a dummy variable South which attenuate the impact of the index. Moreover, if I look at irregular contracts defined with a score of irregularity of 100%, the positive impact of bad credits on irregular part-time contracts (female) is around 0.014 in Services (see Table 14).

For the other economic sector codes, results do not provide evidence of an impact of bad credits on the number of irregular contracts for irregular firms (see Appendix D).

8 Conclusion

High taxes, social security contributions, heavy regulations make irregular work more attractive for firms. In this paper, I construct an irregular job rate using Italian administrative data. Italy represents a good and interesting setting, due to the highest levels of evasion and underground work, and the numerous interventions against shadow economy implemented by Governments. This research analysis uses the INPS dataset, which contains information on the universe of Italian workers, with all the relative characteristics. It is well known how these kinds of flexible contracts, born initially with the objective of being a deterrent for undeclared workers, can represent a good chance for informality. Underground activity is impacted by labour regulations and it is correlated with the level of financial development and credit access. Results confirm that irregular firms tend to hide underground workers taking advantage from non-standard jobs. More specific, I show that irregular workers are covered by non-standard jobs, with a focus on part-time solutions and female workers.

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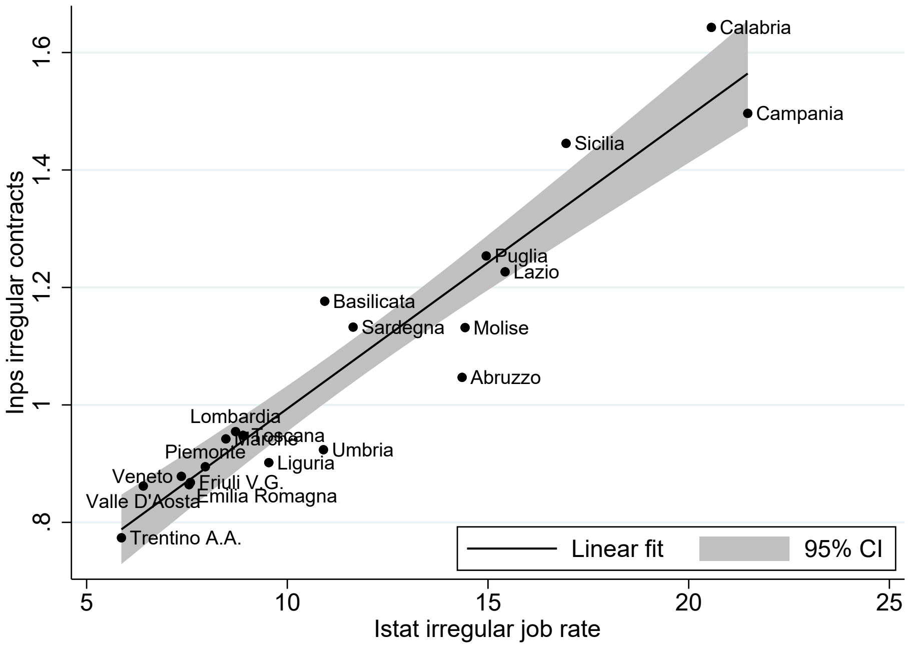
9 Figures and Tables

Figure 1: Comparison between ISTAT and INPS: Part-time contracts



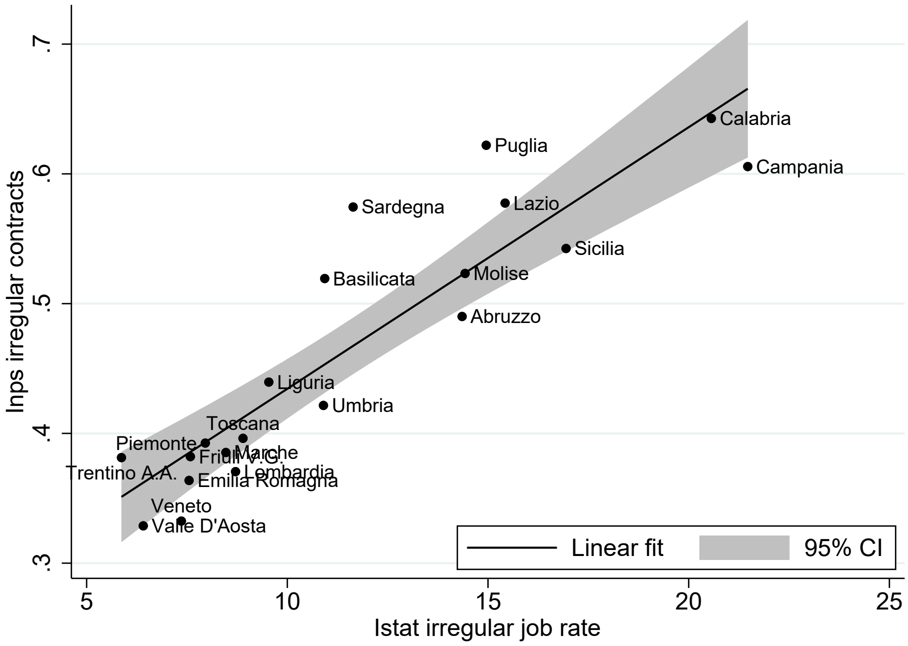
Note. Comparison between ISTAT data and irregular part-time contracts with INPS data. Figure plots the regional averages of the irregular part-time contracts, defined with INPS data according to the score of irregularity, and the irregular job rate provided by ISTAT, based on Labour Force Survey.

Table 1: Correlation ISTAT data - Part-time contracts

	Irr. contracts	ISTAT irr. job rate
Irregular firms	1.0000	
ISTAT irr. job rate	0.9489*	1.0000
	(0.0000)	

Note. I compare INPS irregular firms with ISTAT irregular job rate. I compute Pearson correlation coefficient, ranges from -1 to 1. Closer to 1 means strong correlation. A negative value indicates an inverse relationship (roughly, when one goes up the other goes down). I collapse irregular firms found with INPS data at regional level in order to compare it with ISTAT irregular job rate. Correlation between the two measure is positive, equal to about 90%, and statistically significant. Star(0.05) sig.

Figure 2: Comparison between ISTAT and INPS: Temporary part-time contracts



Note. Comparison between ISTAT data and irregular temporary part-time contracts with INPS data. Figure plots the regional averages of the irregular temporary part-time contracts, defined with INPS data according to the score of irregularity, and the irregular job rate provided by ISTAT, based on Labour Force Survey.

Table 2: Correlation ISTAT data - Temporary part-time contracts

	Irr. contracts	ISTAT irr. job rate
Irregular firms	1.0000	
ISTAT irr. job rate	0.8998*	1.0000
	(0.0000)	

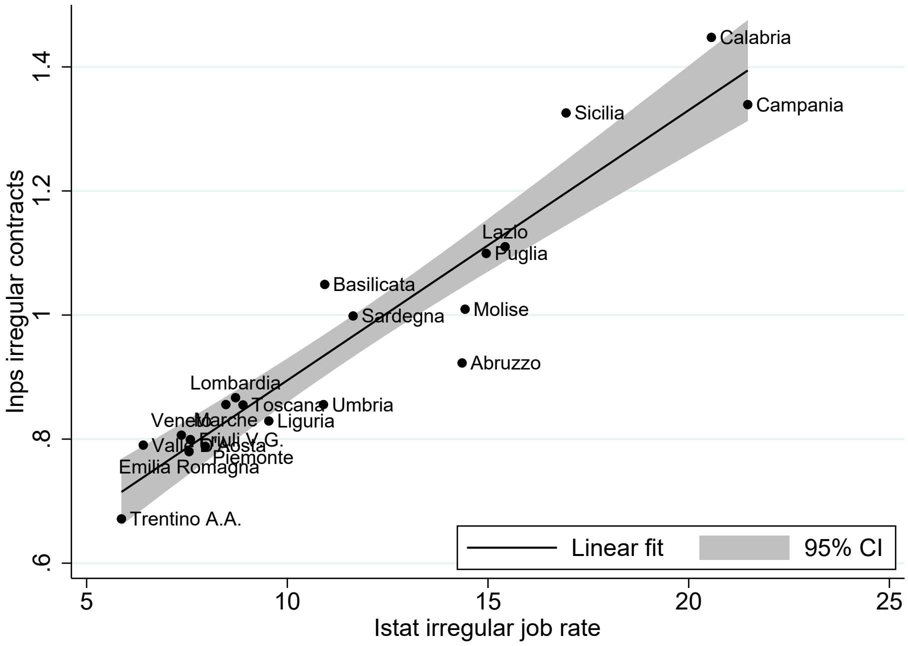
Note. I compare INPS irregular firms with ISTAT irregular job rate. I compute Pearson correlation coefficient, ranges from -1 to 1. Closer to 1 means strong correlation. A negative value indicates an inverse relationship (roughly, when one goes up the other goes down). I collapse irregular firms found with INPS data at regional level in order to compare it with ISTAT irregular job rate. Correlation between the two measure is positive, equal to about 60%, and statistically significant. Star(0.05) sig.

Table 3: Correlation ISTAT data - Temporary full-time contracts

	Irr. contracts	ISTAT irr. job rate
Irregular firms	1.0000	
ISTAT irr. job rate	-0.4214	1.0000
	(0.0643)	

Note. I compare INPS irregular firms with ISTAT irregular job rate. I compute Pearson correlation coefficient, ranges from -1 to 1. Closer to 1 means strong correlation. A negative value indicates an inverse relationship (roughly, when one goes up the other goes down). I collapse irregular firms found with INPS data at regional level in order to compare it with ISTAT irregular job rate. Correlation between the two measure is positive, equal to about 60%, and statistically significant. Star(0.05) sig.

Figure 3: Comparison between ISTAT and INPS: Permanent part-time contracts



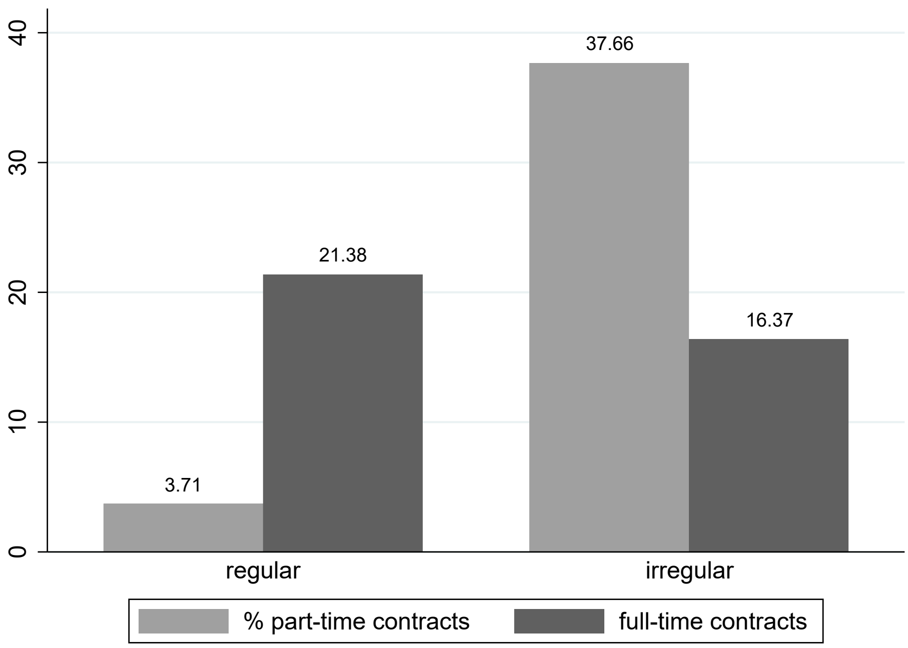
Note. Comparison between ISTAT data and irregular permanent part-time contracts with INPS data. Figure plots the regional averages of the irregular permanent part-time contracts, defined with INPS data according to the score of irregularity, and the irregular job rate provided by ISTAT, based on Labour Force Survey.

Table 4: Correlation ISTAT data - Temporary full-time contracts

	Irr. contracts	ISTAT irr. job rate
Irregular firms	1.0000	
ISTAT irr. job rate	0.9454*	1.0000
	(0.0000)	

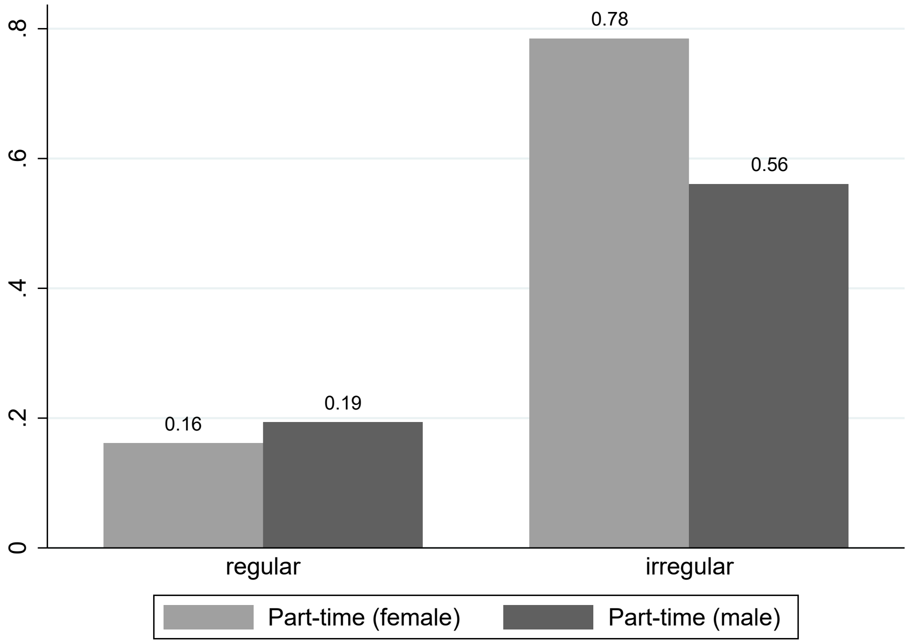
Note. I compare INPS irregular firms with ISTAT irregular job rate. I compute Pearson correlation coefficient, ranges from -1 to 1. Closer to 1 means strong correlation. A negative value indicates an inverse relationship (roughly, when one goes up the other goes down). I collapse irregular firms found with INPS data at regional level in order to compare it with ISTAT irregular job rate. Correlation between the two measure is positive, equal to about 60%, and statistically significant. Star(0.05) sig.

Figure 4: Percentage of part-time and full-time contracts



Note. Figure shows mean of part-time contracts looking at the percentage of part-time, comparing the group of regular and irregular firms.

Figure 5: Part-time contracts, male vs female



Note. Figure compares part-time workers for regular and irregular firms, distinguished for male and female part-time.

Table 5: Part-time contracts, irregular firms

	Manufacturing	Services	Constructions	Commerce
Horizontal	0.956	1.071	0.838	1.11
	(1.541)	(2.630)	(1.123)	(1.871)
Vertical	0.0749	0.142	0.054	0.073
	(0.928)	(0.907)	(0.451)	(0.430)
Mixed	0.052	0.117	0.040	0.076
	(0.579)	(1.408)	(0.382)	(0.535)
Male	0.464	0.641	0.492	0.577
	(1.258)	(2.016)	(1.268)	(1.268)
Female	0.734	0.853	0.526	0.844
	(1.108)	(1.994)	(.675)	(1.465)

Note. Table reports mean and standard deviation (in parenthesis)

Table 6: Part-time contracts, irregular firms

	North-west	North-east	Centre	South	Islands
Horizontal	0.909	0.846	1.050	1.321	1.314
	(2.208)	(1.117)	(1.837)	(2.381)	(3.090)
Vertical	0.095	0.080	0.103	0.103	0.117
	(0.715)	(0.559)	(1.076)	(0.715)	(0.677)
Mixed	0.070	0.068	0.076	0.107	0.122
	(0.975)	(0.466)	(0.634)	(1.547)	(0.909)
Male	0.392	0.353	0.599	0.934	0.918
	(1.290)	(0.877)	(1.676)	(1.994)	(2.544)
Female	0.774	0.742	0.799	0.819	0.831
	(1.961)	(0.949)	(1.249)	(1.590)	(1.760)

Note. Table reports mean and standard deviation (in parenthesis)

Table 7: Irregular firms

	Manufacturing	Services	Constructions	Commerce
Credits	2,077.7	871.89	1,002.8	1,171.2
	(22812.23)	(16272.26)	(7953.22)	(7065.65)
Liquid assets	581.66	406.71	213.019	426.11
	(6441.66)	(21028.91)	(1639.63)	(9906.37)
Total assets	2,833.7	3,491.9	926.77	1,200.8
	(49550.05)	(255170.3)	(16290.6)	(19274.13)
Debts	855.08	1,005.7	569.24	368.798
	(18330.77)	(62145.62)	(12539.9)	(4121.30)
Revenues	7,915.2	3,122.2	2,204.0	6,602.1
	(149312.8)	(55517.58)	(12855.76)	(50076.39)
Labour cost	985.44	833.71	453.46	522.30
	(6116.37)	(25701.85)	(1681.958)	(4082.39)
Value added	1,689.7	1,123.8	619.10	760.10
	(34184.2)	(32821.68)	(2445.281)	(5815.02)
Profits	150.24	54.79	15.25	75.17
	(6553.62)	(5008.17)	(1269.71)	(1700.38)
Roe	13.99	16.08	16.18	14.29
	(20.36)	(23.40)	(22.49)	(20.88)
Roi	3.26	.90	8.28	5.04
	(1323.38)	(370.48)	(67.08)	(157.42)
Roa	5.95	5.87	6.35	5.22
	(7.40)	(8.79)	(7.38)	(7.36)

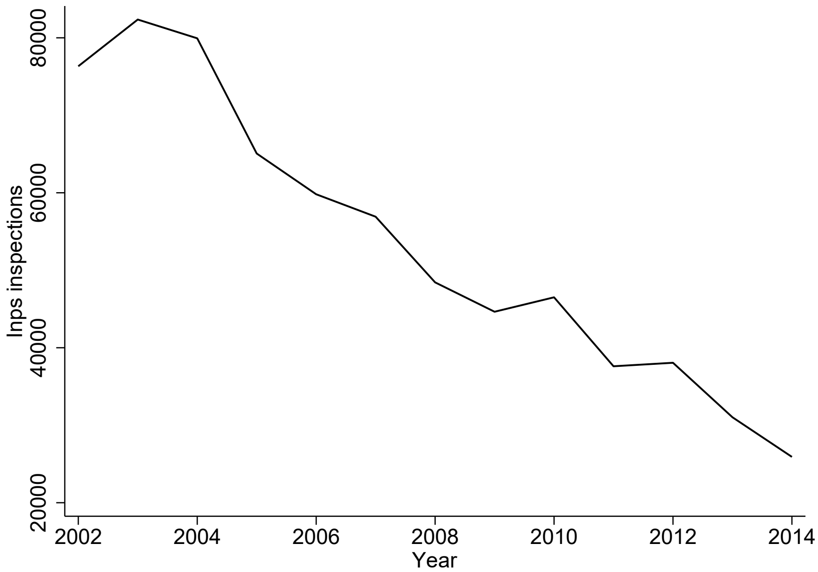
Note. Table reports mean and standard deviation (in parenthesis). Values are expressed in thousands euros.

Table 8: SA index

	Mean	SD	Min	p25	Median	p75	Max
Regular	-3.6	0.57	-43.5	-3.89	-3.60	-3.32	2.8
Irregular	-3.5	0.53	-76.1	-3.82	-3.53	-3.28	5.4

Note. Table reports descriptive statistics of SA index comparing regular and irregular firms. Higher is the index and higher is the probability for a firm to face financial constraints.

Figure 6: INPS inspections 2002-2014



Note. INPS inspections for years 2002-2014. For each firm record, information available is: beginning and end date of the inspections, the number of inspection for each year for each firm the result of the inspection (black workers or not, partial or total irregularities in workers' contracts).

Table 9: Total omissions by economic sector code

	Mean	SD	Obs
Hotels and Restaurants	2,78	15,86	40,5
Public Admin.	15,90	85,71	1,07
Finance	10,33	84,33	3,76
Commerce	7,09	88,072	122,538
Constructions	9,38	62,68	38,258
Energy	8,76	91,25	11,761
Mining	7,62	60,27	262,057
Education	16,82	66,21	1,131
Manufacturing	8,72	65,36	147,484
Health	18,26	110,93	8,873
Services fam.	16,59	595,60	20,975
Services	28,95	206,26	18,059
Transport	22,42	137,93	16,275

Note. Table reports relevant descriptive statistics across types of inspections, in terms of total of omissions found. Data refer to inspections carried out by the Institute between 2002-2014.

Table 10: Irregular firms inspected and not, by years

	Irregular firms			
Years	Inspected	pct	Not Inspected	pct
2012	267,369	25.57	1,349,527	22.20
2013	254,063	24.30	1,426,089	23.46
2014	259,276	24.80	1,600,661	26.33
2015	264,743	25.32	1,702,815	28.01
Total	1,045,451		6,079,092	

Note. Table reports the number of irregular firms which have received at least one inspection by INPS during years available 2012-2015. Irregular firms cover about 25% of inspected firms during the years considered

Figure 7: Irregular firms - Commerce - Year 2015

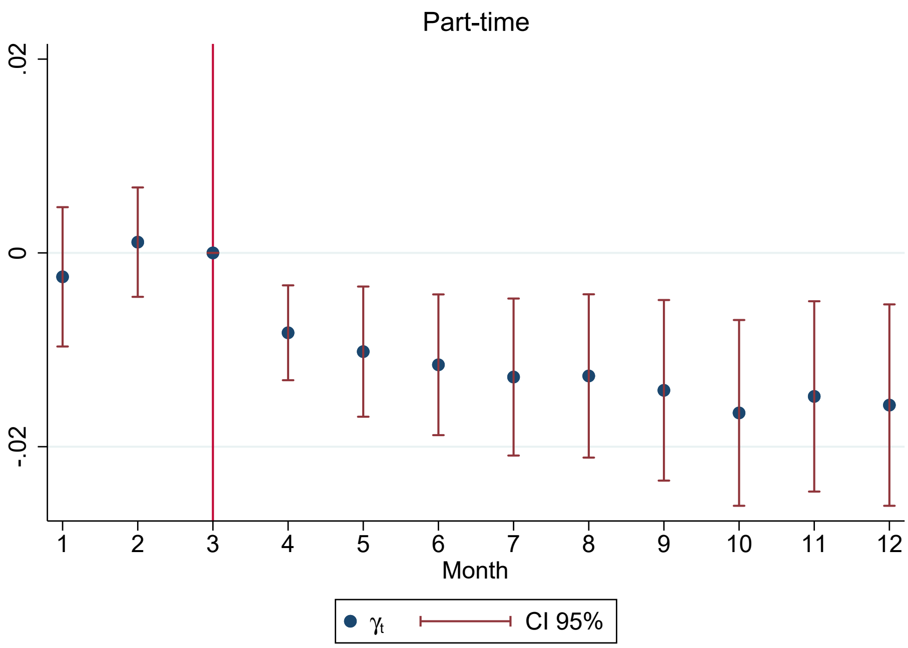


Table 11: Pre-trend Analysis - Irregular firms - Commerce

	Part-time (1)
$T_i \times \mathbb{1}(\text{Month} = \text{January})$	-0.0025
	(0.0044)
$T_i \times \mathbb{1}(\text{Month} = \text{February})$	0.0011
	(0.0034)
$T_i \times \mathbb{1}(\text{Month} = \text{April})$	-0.0082***
	(0.0030)
$T_i \times \mathbb{1}(\text{Month} = \text{May})$	-0.0102**
	(0.0041)
$T_i \times \mathbb{1}(\text{Month} = \text{June})$	-0.0115**
	(0.0044)
$T_i \times \mathbb{1}(\text{Month} = \text{July})$	-0.0128***
	(0.0049)
$T_i \times \mathbb{1}(\text{Month} = \text{August})$	-0.0127**
	(0.0051)
$T_i \times \mathbb{1}(\text{Month} = \text{September})$	-0.0142**
	(0.0057)
$T_i \times \mathbb{1}(\text{Month} = \text{October})$	-0.0165***
	(0.0058)
$T_i \times \mathbb{1}(\text{Month} = \text{November})$	-0.0148**
	(.0060)
$T_i \times \mathbb{1}(\text{Month} = \text{December})$	-0.0157**
	(0.0063)
Month FE	Yes
Firms FE	Yes
Adjusted R^2	0.780
Observations	2,881,866

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 8: Irregular firms (100%) - Services - Year 2015

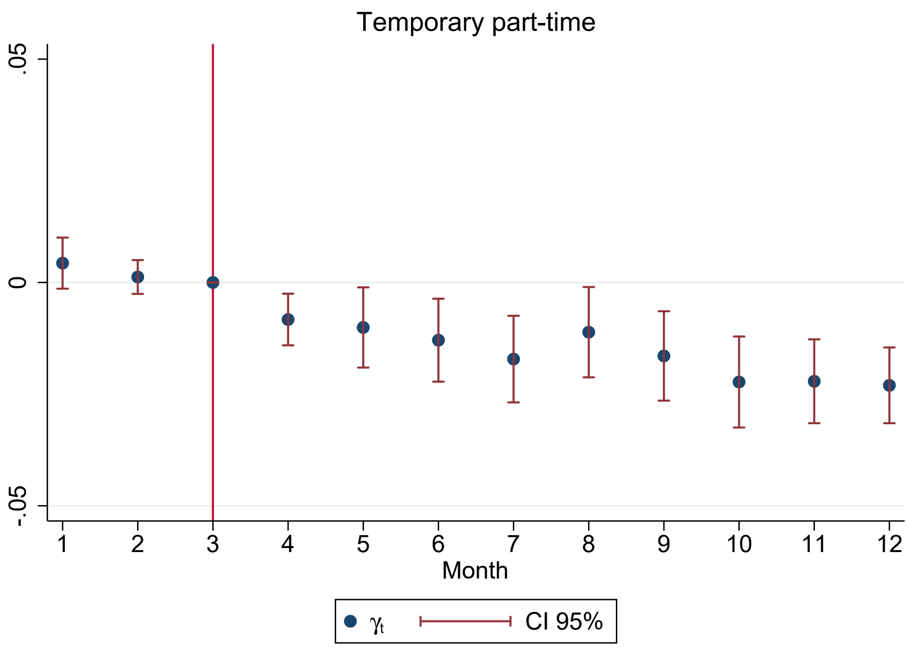


Table 12: Pre-trend Analysis - Irregular firms (100%) - Services

	Temporary part-time
	(1)
$T_i \times \mathbb{1}$(Month = January)	0.0043
	(0.0035)
$T_i \times \mathbb{1}$(Month = February)	0.0012
	(0.0023)
$T_i \times \mathbb{1}$(Month = April)	-0.0083**
	(0.0035)
$T_i \times \mathbb{1}$(Month = May)	-0.0101*
	(0.0055)
$T_i \times \mathbb{1}$(Month = June)	-0.0129**
	(0.0056)
$T_i \times \mathbb{1}$(Month = July)	-0.0172***
	(0.0059)
$T_i \times \mathbb{1}$(Month = August)	-0.0111*
	(0.0061)
$T_i \times \mathbb{1}$(Month = September)	-0.0165***
	(0.0061)
$T_i \times \mathbb{1}$(Month = October)	-0.0223***
	(0.0062)
$T_i \times \mathbb{1}$(Month = November)	-0.0221***
	(0.0057)
$T_i \times \mathbb{1}$(Month = December)	-0.0230***
	(0.0052)
Month FE	Yes
Firms FE	Yes
Adjusted R^2	0.540
Observations	2,881,866

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Estimation results - Services

	Part-time	Temp.pt	Pt(female)	Pt(male)	Perm.pt
	(1)	(2)	(3)	(4)	(5)
Financial Development	0.008	-0.001	0.009***	0.003	0.009
	(0.007)	(0.005)	(0.003)	(0.007)	(0.006)
GDP	9.27e-06	3.81e-06	2.61e-06	7.81e-06	7.67e-06
	(2.23e-06)	(1.70e-06)	(6.17e-07)	(2.59e-06)	(2.15e-06)
Unemployment rate	0.033	0.016	0.010	0.033	0.031
	(0.008)	(0.004)	(0.002)	(0.007)	(0.006)
South	0.167	0.063	0.022	0.172	0.089
	(0.097)	(0.055)	(0.038)	(0.086)	(0.082)
Age	-0.375	-0.334	-0.152	-0.374	-0.188
	(0.058)	(0.055)	(0.030)	(0.048)	(0.032)
Age2	0.054	0.052	0.020	0.058	0.018
	(0.011)	(0.010)	(0.007)	(0.008)	(0.006)
Constant	0.929	0.806	0.845	0.499	0.018
	(0.127)	(0.105)	(0.050)	(0.118)	(0.006)
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0082	0.0035	0.0020	0.0144	0.0119
Observations	2,596,536	2,596,536	2,596,536	2,596,536	2,596,536

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Estimation results - Irregular firms at 100% in Services

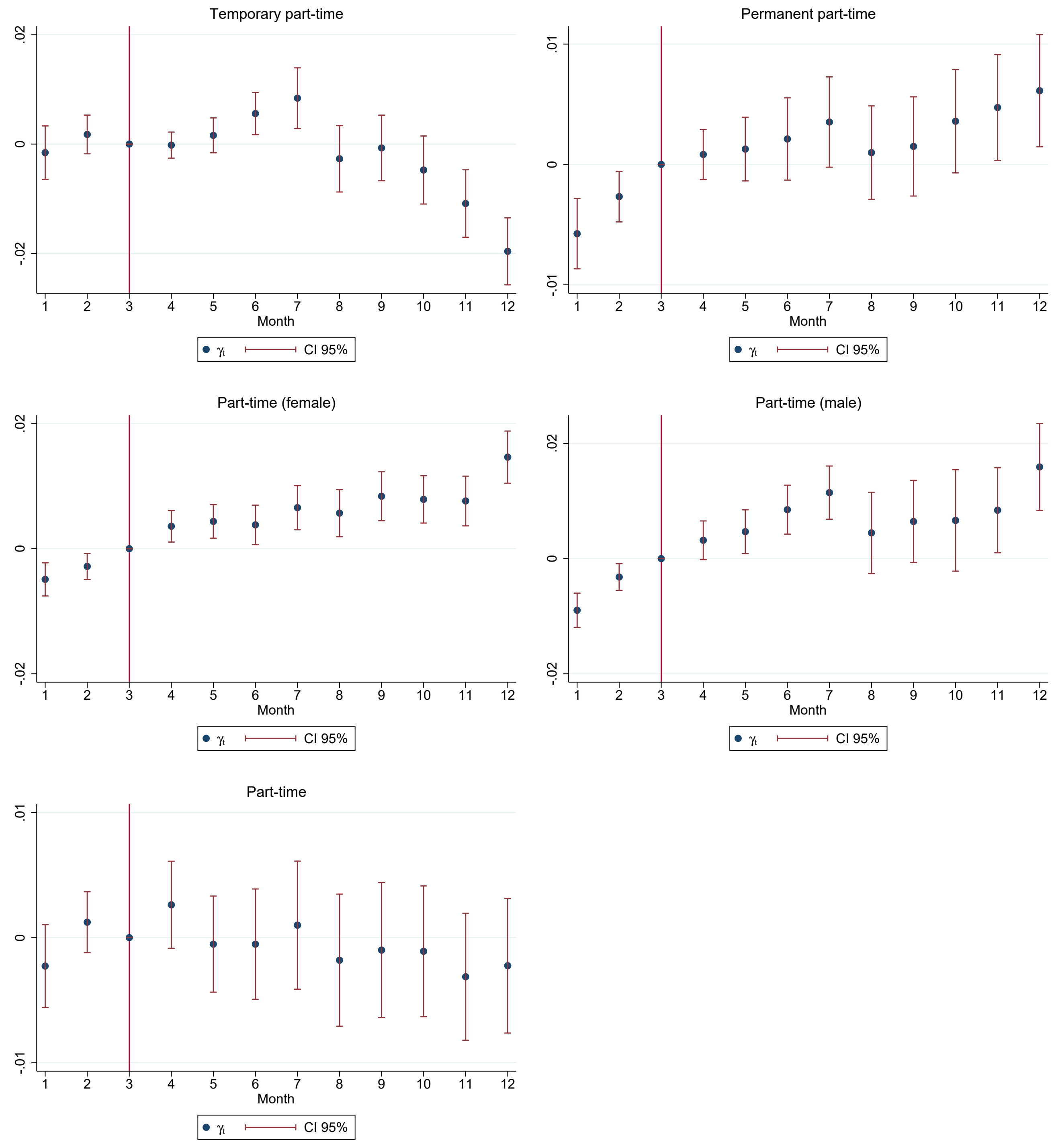
	Part-time	Temp.pt	Pt(female)	Pt(male)	Perm.pt
	(1)	(2)	(3)	(4)	(5)
Financial Development	0.013	0.005	0.014*	-0.0007	0.010
	(0.013)	(0.005)	(0.007)	(0.0102)	(0.011)
GDP	9.70e-06	2.08e-06	-3.98e-07	.0000103	8.87e-06
	(2.55e-06)	(7.55e-07)	(1.36e-06)	(3.52e-06)	(2.23e-06)
Unemployment rate	0.046	0.008	0.001	0.044	0.039
	(0.011)	(0.004)	(0.005)	(0.010)	(0.009)
South	0.218	-0.051	-0.005	0.227	0.261
	(0.126)	(0.055)	(0.066)	(0.127)	(0.107)
Age	-0.715	-0.333	-0.242	-0.488	-0.473
	(0.165)	(0.091)	(0.086)	(0.124)	(0.125)
Age2	0.124	0.042	0.055	0.071	0.094
	(0.030)	(0.015)	(0.015)	(0.022)	(0.023)
Constant	1.764	0.606	1.399	0.386	1.304
	(0.229)	(0.124)	(0.141)	(0.172)	(0.186)
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0102	0.0023	0.0005	0.0306	0.0208
Observations	701,602	701,602	701,602	701,602	701,602

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Irregular firms

Figure 9: Irregular firms



B Irregular firms, by economic sector codes

Figure 10: Commerce

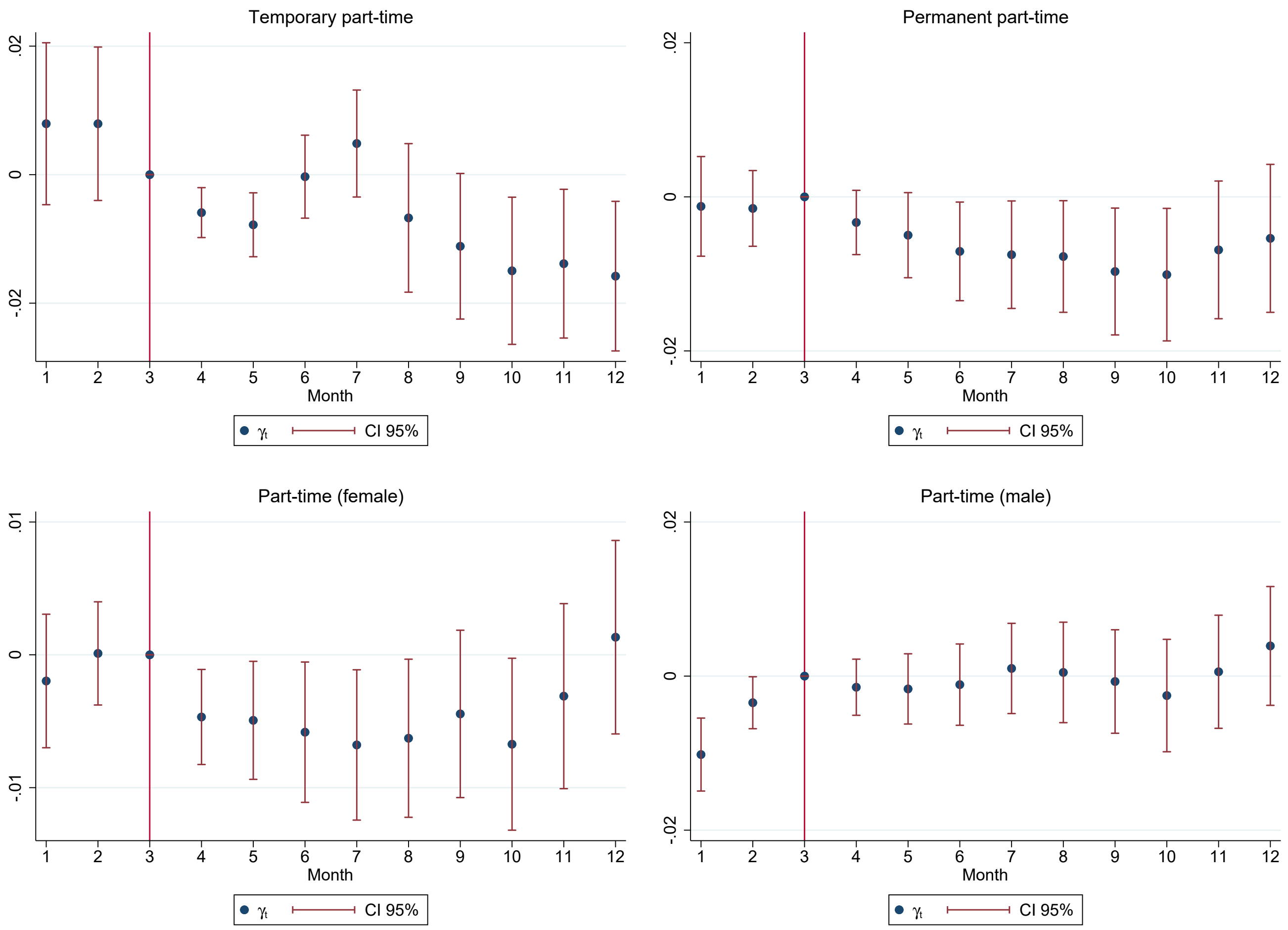


Figure 11: Construction

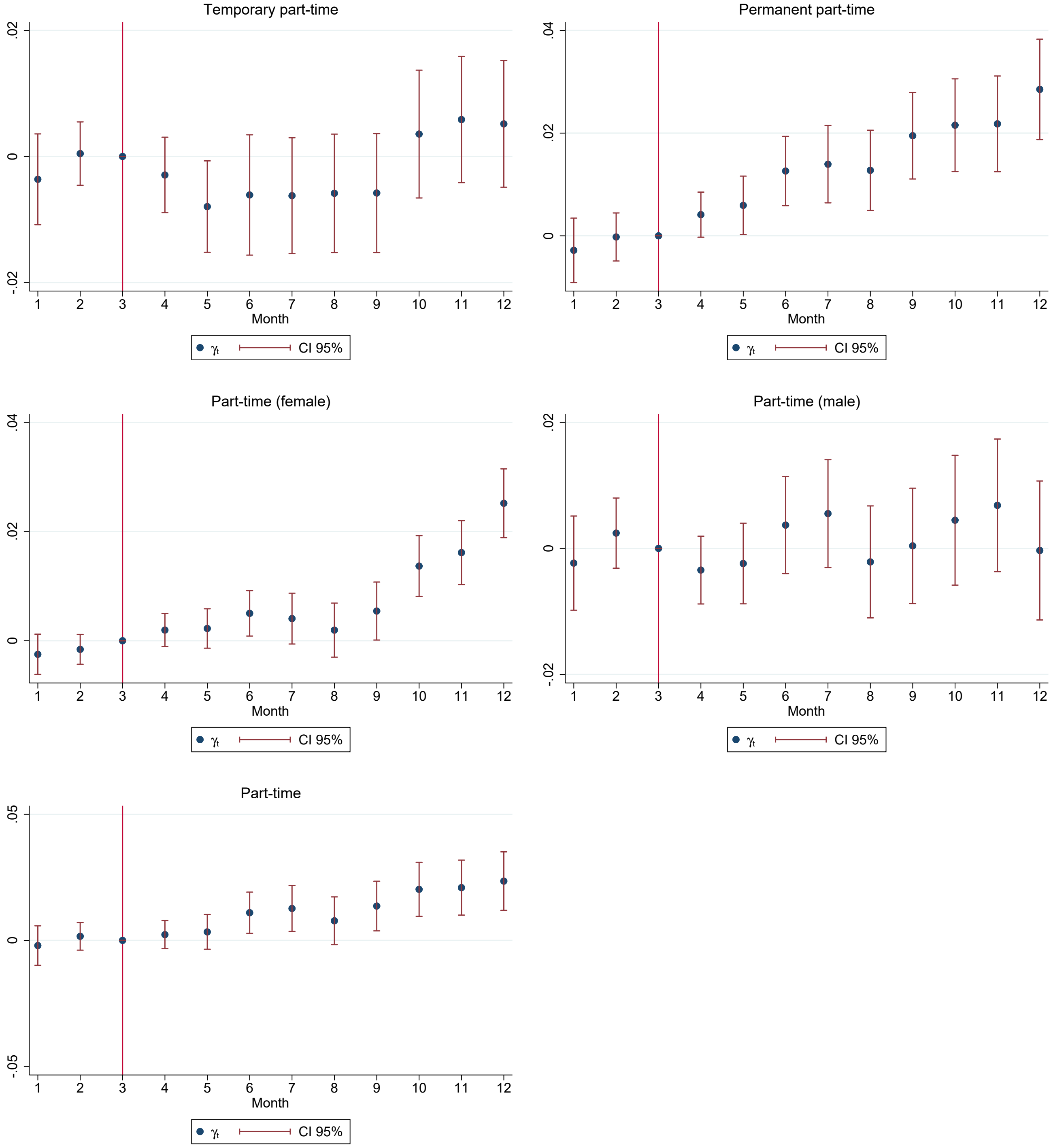


Figure 12: Manufacturing

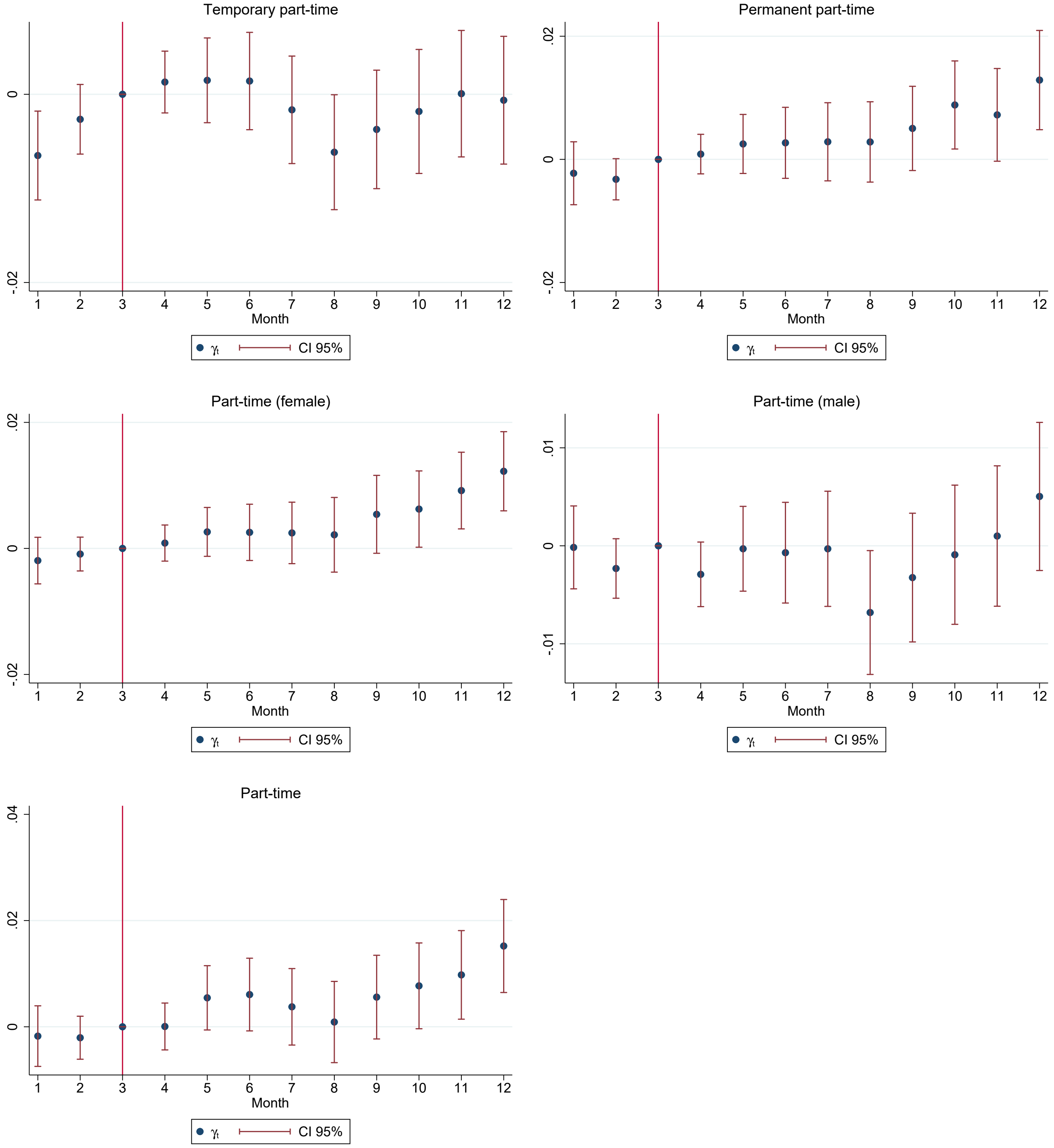
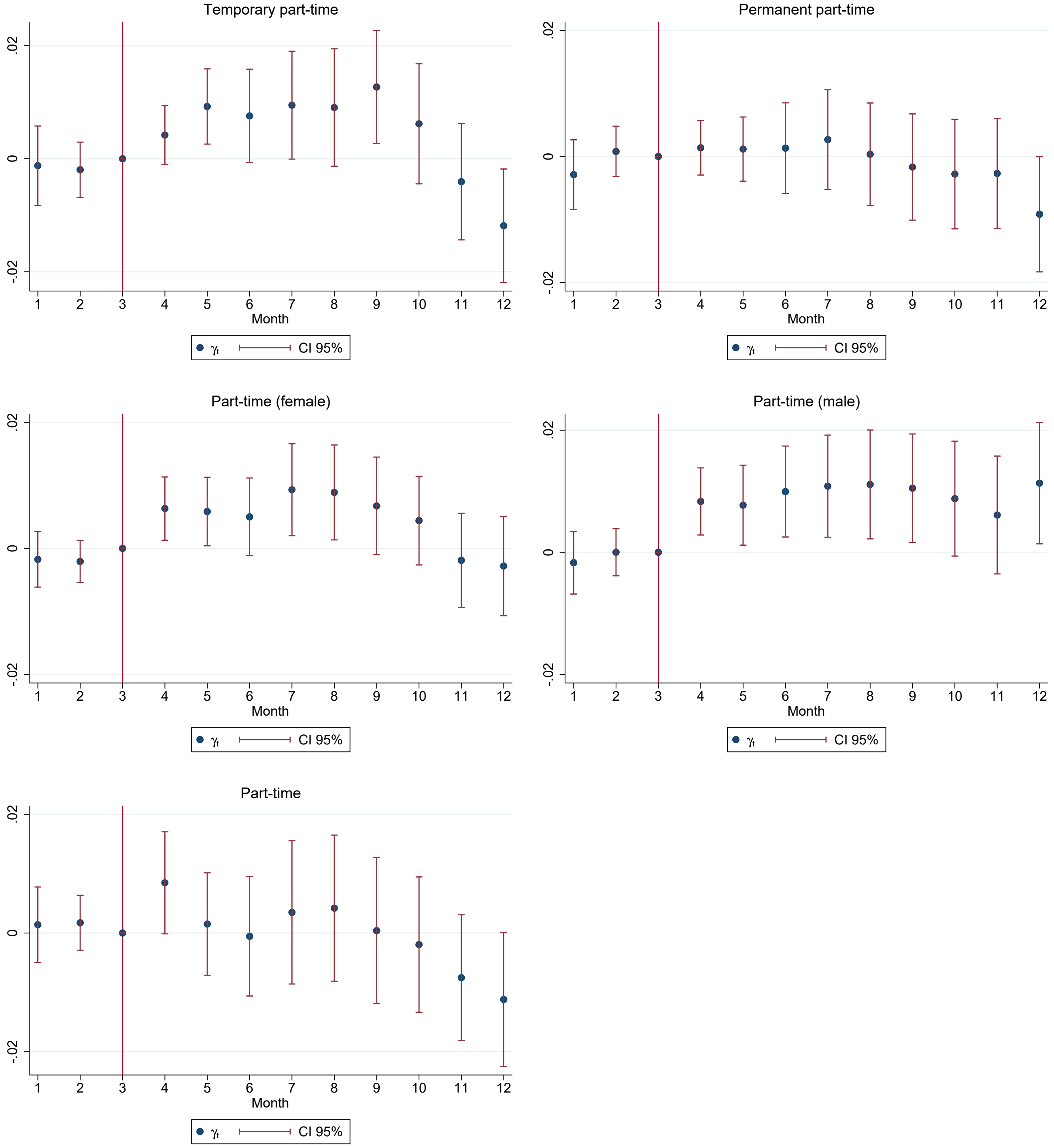


Figure 13: Services



C Irregular firms, by economic sector codes and 100% score of irregularity

Figure 14: Services

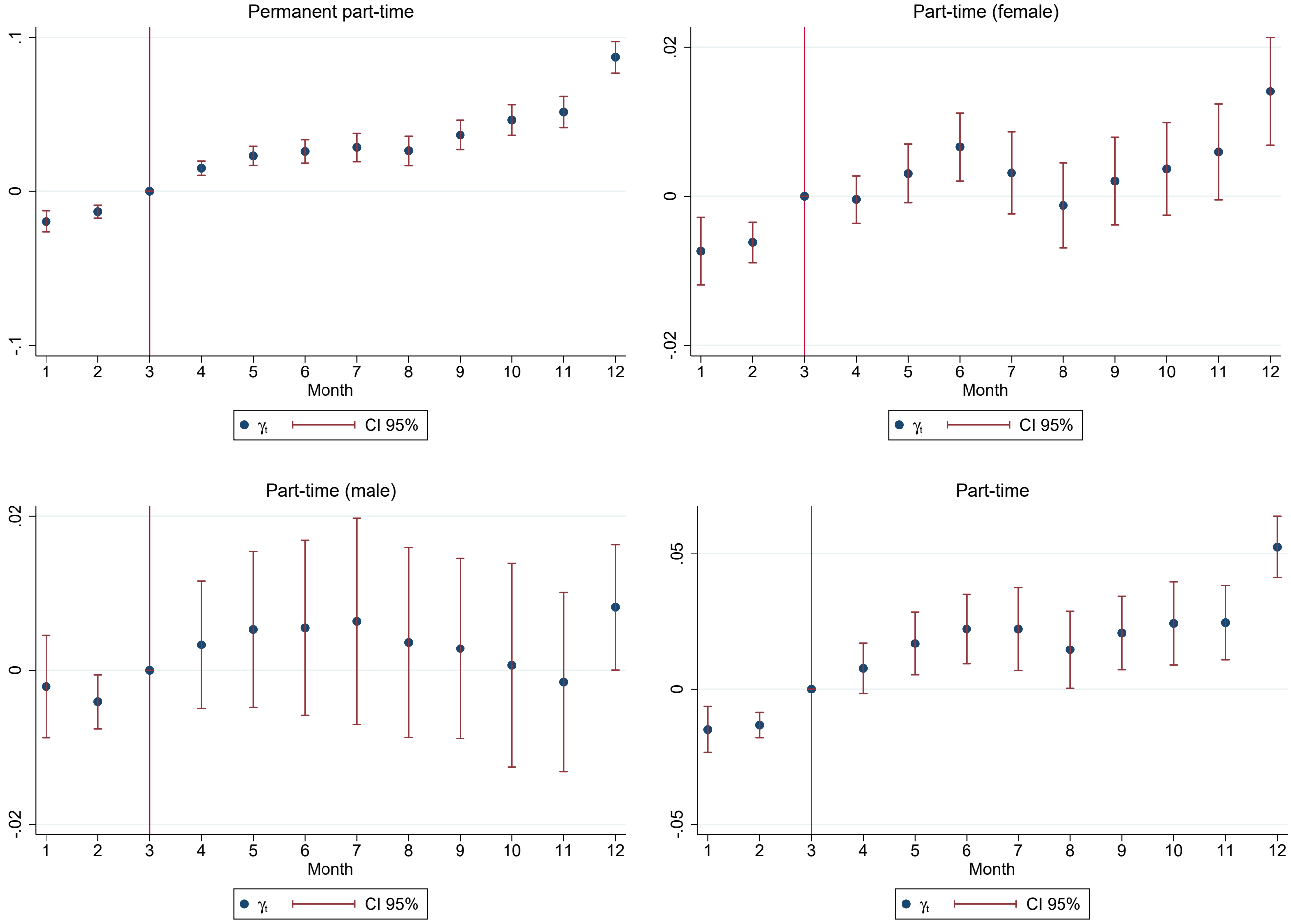


Figure 15: Commerce

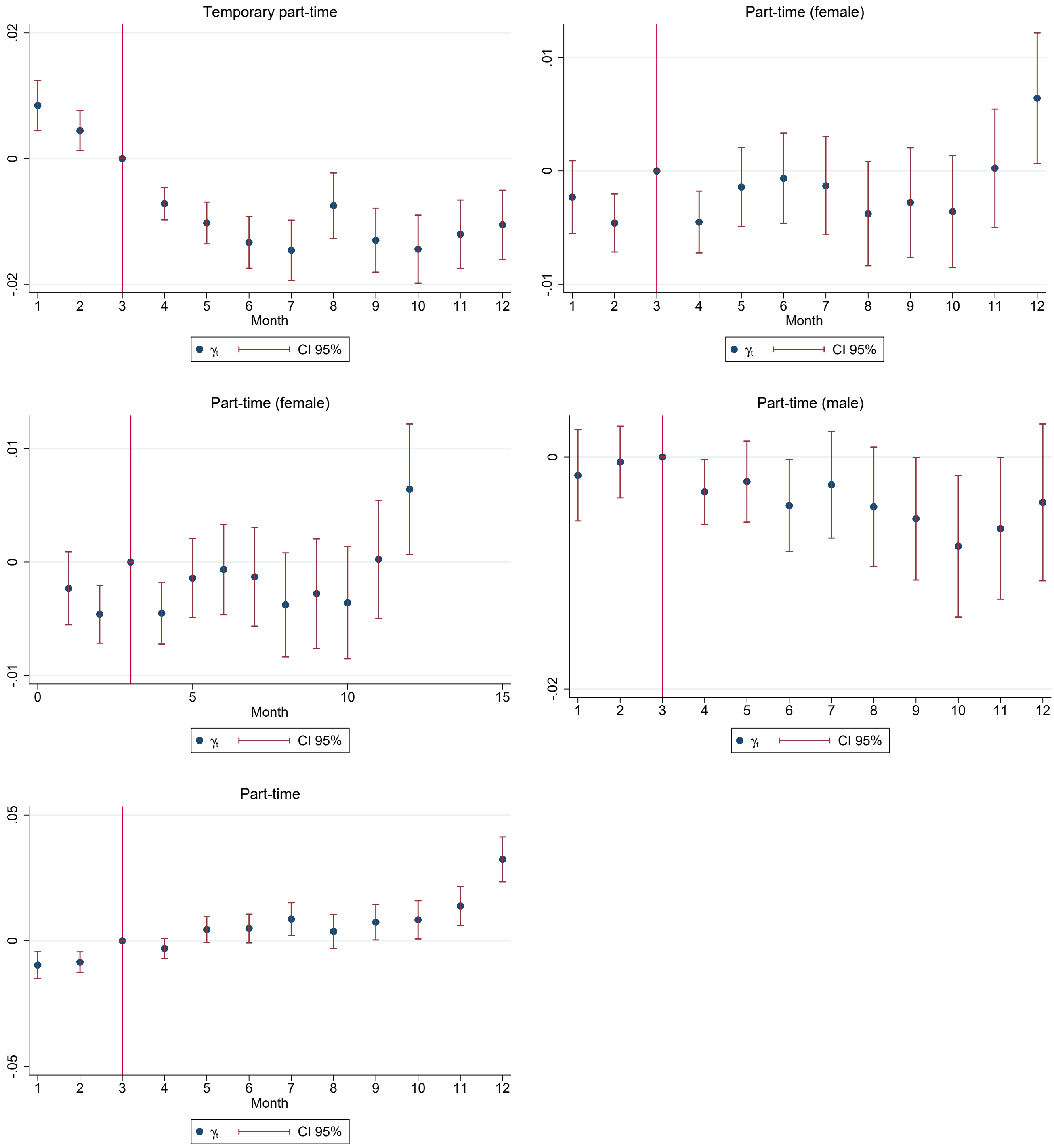


Figure 16: Construction

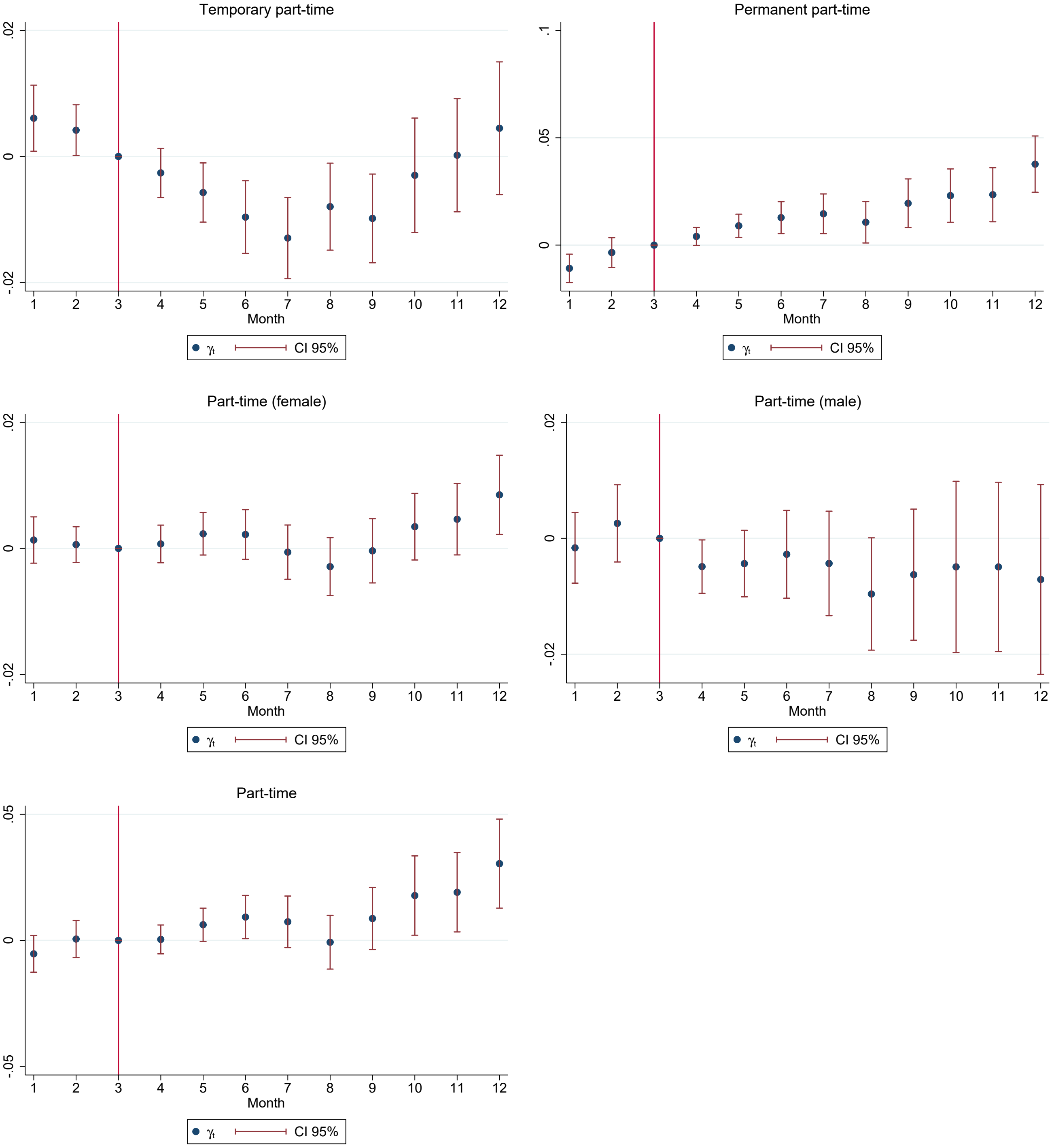
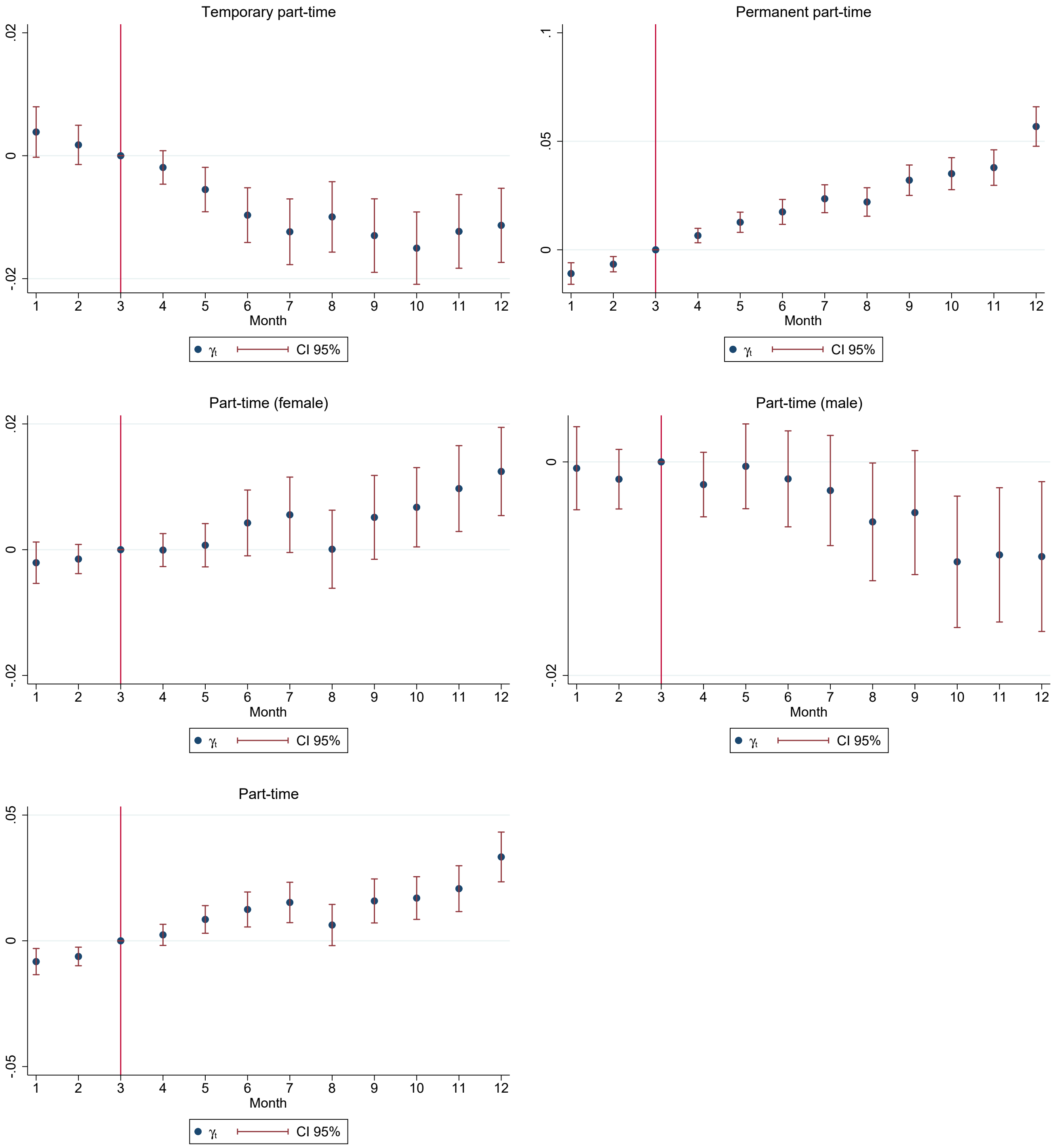


Figure 17: Manufacturing



D Financial development, additional results

Table 15: Estimation results - Commerce

	Part-time	Temp.pt	Pt(female)	Pt(male)	Perm.pt
	(1)	(2)	(3)	(4)	(5)
Financial Development	0.001	-0.001	-0.000	0.0003	-0.0006
	(0.006)	(0.004)	(0.003)	(0.006)	(0.0068)
GDP	4.20e-06	6.47e-07	2.31e-06	2.32e-06	2.89e-06
	(2.17e-06)	(2.12e-06)	(6.99e-07)	(3.00e-06)	(2.26e-06)
Unemployment rate	0.031	0.012	0.007	0.032	0.031
	(0.004)	(0.005)	(0.002)	(0.005)	(0.004)
South	0.119	0.010	0.030	0.144	0.099
	(0.057)	(0.080)	(0.044)	(0.056)	(0.059)
Age	-0.195	-0.237	-0.165	-0.083	-0.117
	(0.026)	(0.073)	(0.020)	(0.022)	(0.025)
Age2	0.023	0.035	0.025	0.006	0.015
	(0.006)	(0.019)	(0.004)	(0.004)	(0.006)
Constant	0.918	0.641	0.922	0.227	0.725
	(0.109)	(0.099)	(0.044)	(0.123)	(0.109)
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0170	0.0027	0.0023	0.0356	0.0220
Observations.	1,801,304	1,801,304	1,801,304	1,801,304	1,801,304

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Estimation results - Construction

	Part-time	Temp.pt	Pt(female)	Pt(male)	Perm.pt
	(1)	(2)	(3)	(4)	(5)
Financial Development	0.003	0.0009	-0.007	0.009	0.0009
	(0.005)	(0.0033)	(0.003)	(0.007)	(0.0053)
GDP	4.41e-06	5.68e-06	-2.91e-06	.0000106	2.19e-06
	(3.55e-06)	(2.84e-06)	(1.63e-06)	(6.48e-06)	(2.55e-06)
Unemployment rate	0.023	0.013	-0.012	0.044	0.018
	(0.006)	(0.004)	(0.003)	(0.010)	(0.004)
South	-0.037	0.030	-0.084	0.072	-0.053
	(0.062)	(0.036)	(0.030)	(0.091)	(0.050)
Age	-0.0175707	-0.060	0.087	-0.117	0.035
	(0.034)	(0.019)	(0.017)	(0.039)	(0.032)
Age2	0.004	0.008	0.002	0.012	0.000
	(0.009)	(0.004)	(0.004)	(0.009)	(0.008)
Constant	0.474	0.031	0.544	-0.166	0.392
	(0.140)	(0.118)	(0.073)	(0.256)	(0.105)
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0065	0.0042	0.0353	0.0319	0.0060
Observations.	714,761	714,761	714,761	714,761	714,761

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Estimation results - Manufacturing

	Part-time (1)	Temp.pt (2)	Pt(female) (3)	Pt(male) (4)	Perm.pt (5)
Financial Development	-0.004	0.001	0.000	-0.006	-0.005
	(0.007)	(0.002)	(0.003)	(0.006)	(0.007)
GDP	3.57e-06	-1.23e-06	-4.43e-08	3.25e-06	3.67e-06
	(1.48e-06)	(7.52e-07)	(7.40e-07)	(2.12e-06)	(1.50e-06)
Unemployment rate	0.030	0.005	-0.003	0.039	0.028
	(0.005)	(0.002)	(0.001)	(0.006)	(0.005)
South	0.223	0.120	0.013	0.281	0.160
	(0.059)	(0.029)	(0.025)	(0.064)	(0.053)
Age	-0.132	-0.129	-0.004	-0.176	-0.070
	(0.038)	(0.018)	(0.021)	(0.036)	(0.035)
Age2	0.017	0.019	0.006	0.023	0.010
	(0.007)	(0.003)	(0.004)	(0.006)	(0.007)
Constant	0.749	0.472	0.700	0.214	0.555
	(0.085)	(0.039)	(0.043)	(0.116)	(0.085)
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0179	0.0097	0.0007	0.0484	0.0143
Observations.	2,007,627	2,007,627	2,007,627	2,007,627	2,007,627

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$