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Abstract

In this paper we discuss the time series properties of a novel daily series of aggregate employment creation and destruction as registered by the Social Security in Spain. We focus on the period of economic recovery after the 2012 Labour Reform. Our aim is to disentangle the role of key economic factors face to face observed calendar effects. While calendar effects are mostly associated to the incentives for firms to avoid labour costs due to employment legislation, there seem to be determinants of their quantitative importance related to the sectoral composition of the economy and to business cycle fluctuations. First, we identify calendar effects in job flows and we single out the Monday effect: an overreaction in job creation at the beginning of the workweek. Then we investigate the importance of calendar effects for aggregate employment dynamics. We find asymmetry between a "normal" state most of the time, and a state of low growth by the end of every month, which is more intense the second half of the year and while the economy is booming. Finally, we use the register of contracts at the micro level to evaluate how the occupational structure determines the variability of calendar effects over time. Our findings suggest that a move towards a unique contract will dramatically modify the determinants and some of the consequences of temporary employment in Spain.

Keywords: Employment flows, fixed-term contracts, calendar effects, business cycle fluctuations, sectoral composition, regime shifts
JEL Classification: J23, E24, C22

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1 Introduction

The Spanish labour market has a dual contractual structure originated in 1984 with the liberalization of the use of fixed-term contracts. Since then, and despite the seven labour reforms implemented, Spain has an unjustifiably high rate of temporary employment. Before the crisis of 2008, Spain was the OECD country with the highest proportion of temporary jobs with one out of three workers. Notwithstanding the massive destruction of more than 40% of those jobs during the crisis, the Spanish economy registered record rates of temporary employment by the beginning of the recovery after a deep and long lasting recession. As temporary contracts affect to more than 25% of wage earners such a situation is a pressing issue that requires better understanding.[1]

In this paper we want to contribute to our understanding of this dual labour model by looking to aggregate high frequency data. We combine the aggregate employment data with the register of new contracts by occupations, and we focus on the huge daily flows of creation and destruction of jobs observed in the Spanish economy after the last labour reform. The traditional factors behind employment volatility persist though. In economic booms Spanish productive model generates strong job creation, albeit concentrated in low-productivity industries, whereas in recessions it exacerbates job destruction. Firms respond to economic fluctuations through labour turnover, rather than looking for alternatives such as changes in workplace organization or wages. In that context we show that substantial labour turnover occurs on a daily basis and is intensified at recurrent dates along the calendar year. Such a phenomenon has been long discussed in the labour market literature for different countries with lower frequency data. Here, we take advantage of a novel daily series of social security affiliations to precisely identify calendar effects, that is, job creation and destruction dependent on the day of the week or the month. Moreover, we illustrate that the quantitative importance of calendar effects is related to the sectoral composition of the economy and to business cycle fluctuations. This circumstance affects employment dynamics and make the use of monthly data problematic for time series purposes or to nowcast activity.

The 2012 reform targeted labour costs to support "internal devaluation" (i.e. encourage wage

[1]The institutional factors that give rise to the high incidence of temporary employment in Spain are precisely discussed in Dolado et al. (2002), Bentolila et al (2008 and 2012) and Costain et al (2010), among others. For labour demand related factors see, for instance, Benito and Hernando (2008). Recently, Felgueroso et al. (2017) estimate that less than one tenth of temporary contracts became permanent in 2016, with an average duration that felt to 50.6 days in 2016 from around three months in 2006. As early as Blanchard (2004), inspired by Blanchard and Tirole (2003), the proposal of a single open-ended contract for new hires is being discussed to fix this issue.

moderation). That is, the labour reform was designed to make it easier for firms to dismiss insiders to encourage them to accept lower wages. At the same time, the reform promoted internal flexibility so the firms could use other ways to adjust employment (different from external correction) in order to reduce the "duality". It is too soon to analyze the effects of this labour reform, approved on 10th of February 2012 by the Minister Council. Recent work [cf. Izquierdo et al (2013) and Garcia-Pérez and Doménech (2017)] shows that the reform has had some impact on wage moderation but it has hardly affected the duality.

The data we use can complement the micro evidence on duality after the reform. First, the daily social security registers collect information of start and end of all employment spells (both self-employed and employed workers). Notice that in 2016 more than 26 millions of new registers (and 25.5 million of deregisters) have been recorded in the Social Security database. This means that the number of new registers every year can be as high as 1.5 times the stock of workers affiliated to the Social Security. On a daily basis the numbers are also astonishing: on average more than 100,000 new registers and about 100,000 deregisters. It can be easily anticipated that most of the volatility in the job creation and destruction data is generated by excessive use of fixed-term contracts. Methodological changes suggest we restrict to the period after the last labour reform.

In addition, to track the sectoral composition of employment, we use the register of contracts at SEPE (Servicio Público de Empleo Estatal/Official Employment Information Administration) of the Ministerio de Trabajo y Seguridad Social (MESS, Spanish Ministry of Employment and Social Security) on a daily basis. The reason is that affiliation data by sector or occupation are not available. The drawback of using registered contracts in its turn is to exclude self-employed workers. We contrast the time series properties of employment creation with those of new contracts, and the main finding is the register of self-employed goes up when new contracts shrink. Then, to see what we learn on calendar effects from the sectoral composition of the economy, we arrange about 100 million new contracts from January 2011 to August 2017 across the different occupations in the MESS classification at two digits. Notice that SEPE classification of occupations differs from the International Standard Classification of Occupations, so we summarize our use in the Appendix.[2]

As we shall see, casual observation suggests strong calendar effects by the beginning and the end

[2]SEPE has allowed us to use its statistics of contracts on the basis of a research agreement with Fedea. We are very grateful to have access to this disaggregated data. Unfortunately, we can only approximate the disaggregation of job creation in Social Security by the new contracts registered at SEPE, as Social Security does not offer access to their disaggregated data of job creation and destruction.

of the week, and by the beginning and the end of the month. The daily data allow us to identify the strength of these calendar effects, how they change over time, and the way in which they are different for the flows of creation and destruction. Thus, in the first part of the paper we analyze the calendar effects on aggregate job flows over the period 2012-2017 using time series methodology. The finding is that not all of the many calendar effects that can be described on daily data are alike. Most of the episodic variation in the series comes from the patterns of creation and destruction of very short term contracts. We identify Mondays and Fridays as key days in the process of job creation and destruction by firms. However, the importance of the Monday effect clearly dominates, both for the start and the end of employment spells. Also, the interaction of the effect at the beginning and end of the week with the beginning and end of the month is key. We find asymmetry between two states of employment: a "normal" state most of the time, and a state of low growth by the end of every month. Moreover, the regime shifts we measure (Markov-Switching model) are more intense during the second part of the year all of the years, and they are intensified the more the economy moves onto the expansion period. This latter finding can be related to regional business cycle evidence discussed, e.g. in Camacho et al. (2017), which shows that the Islands and Valencia typically lead the cycle. In these regions the incidence of tourism employment is large, and this productive model represents well booms and busts in Spain. We consider this feature a way to rationalize the interaction of the end of month effect with the business cycle we spot.

In the second part of the paper we explore the determinants of the strength and variability of the calendar effects described in the first part by using the universe of contracts registered in Spain. The goal is to identify highly temporary occupations for which labour market policy should devote special attention, either in the form of active policies or in terms of human auditing. We consider that focusing on selected occupations is key to mitigate the high incidence/potentially inefficient temporary contracts. Precisely, we find that that occupations with stronger Monday effects exhibit relatively high temporary rates. Our analysis is not only able to identify which sectors are responsible for the high level of precarious jobs in Spain, but also at what moments of the calendar year the excessive use of temporary hiring by these sectors is higher.

Several authors have organised the micro evidence on the determinants of temporary employment and the transitions towards regular employment in Spain. A main part of the literature has established that temporary contracts fail to act as stepping-stones to regular employment for many labour market entrants, as Amuedo-Dorantes (2000), García-Pérez and Muñoz-Bullón (2011), Ar-

ranz and García-Serrano (2014) and Bonhomme and Hospido (2017), among others. It is not strange then to see replacement behaviour in employment. Nagore and van Soest (2017) and Bentolila et al (2017) show how fixed-term contracts help to reduce the risk of long term unemployment, but at the same time drive huge inflows into unemployment. Güell and Petrongolo (2007) focus on the institutional arrangements, while Felgueroso et al (2017) discuss the way in which shorter contracts and frequent unemployment spells affect the transitions from temporary to permanent employment. As these authors, we investigate the prevalence of short fixed-term contracts. Different from them we retain that calendar effects are an important driver of contracts, whose intensity varies across time and occupations as far as working days are linked to daily economic activity. Finally, the novelty for the short-term movements we analyze is deterministic effects, rather than conditional variance as it is the case with financial daily data. Consequently, the time series methods we present should be of interest for related applications with daily macroeconomic data under asymmetries.[3]

The organization of the paper is as follows. We start by introducing the daily employment data. Section 2 describes the social security and the contracts registers, and introduces the importance of calendar effects. Section 3 moves forward to the focus of our paper which is the analysis of the deterministic components associated to the calendar of job creation and job destruction in Spain. In Section 4 we explore the consequences of the calendar effects identified on aggregate employment dynamics, that is, the time series dimension. In particular, we implement a Markov-Switching model for the changes in the employment stock. Section 5 explores the role of the sectoral composition of contracts to account for the variability associated to the calendar effects thus identified, that is, the cross-sectional aspect. Section 6 concludes.

2 The dataset and the institutional arrangement

In this paper we use two sources of data. First we use the aggregate register of affiliations in Social Security. This includes the figures for aggregate employment creation and destruction in the Spanish economy on a daily basis for both employed and self-employed workers. The homogeneous sample we consider covers the period 2012-2017. Secondly, as far as affiliation data by sector or occupation are not available, we use instead the micro data on new contracts registered by the

[3]Calendar effects have been extensively discussed in finance (Berument and Kiymaz, 2001) to analyze market volatility along the week. The availability of daily data brings about questions relevant for consumption and retail sales analysis, forecasting, or macroeconomics [cf. Soares-Esteves and Rodrigues (2010) and Verbaan et al. (2017)].

Spanish Ministry of Employment and Social Security through the SISPE (Sistema de Información de los Servicios Públicos de Empleo/Official Register of Employment). The disaggregated dataset contains information on the starting dates of all employment spells occurred in Spain. Using these dates we aggregate the contracts figure for comparison with the daily employment creation data. Notice that the register of contracts do not cover self-employed workers. A description of the sources and methods used in our data construction is given in the Appendix.[4]

The identification of calendar effects is particularly important for the social security affiliation data. In the literature, it is common to consider differences along *i)* the day of the week, *ii)* the month of the year, and *iii)* holidays, as we do. We will see that the intra-month profile is not key for the duration of contracts, but rather, it is key to focus on the coincidence of the beginning and end of the week and the month. In addition, the register of affiliations only occurs on weekdays. That is, the register data will only coincide with the actual data if the starting or the termination date of a contract occurs on a weekday. Rather, if the starting date or the termination date is either during the weekend or in a bank holiday, the register will be recorded on the first subsequent weekday. Consequently, there will be calendar effects related to the distortion associated to the register being closed during the weekend and bank holidays. This is relevant for what we will call below the *Monday effect*, so we distinguish mondays from the beginning of the week.

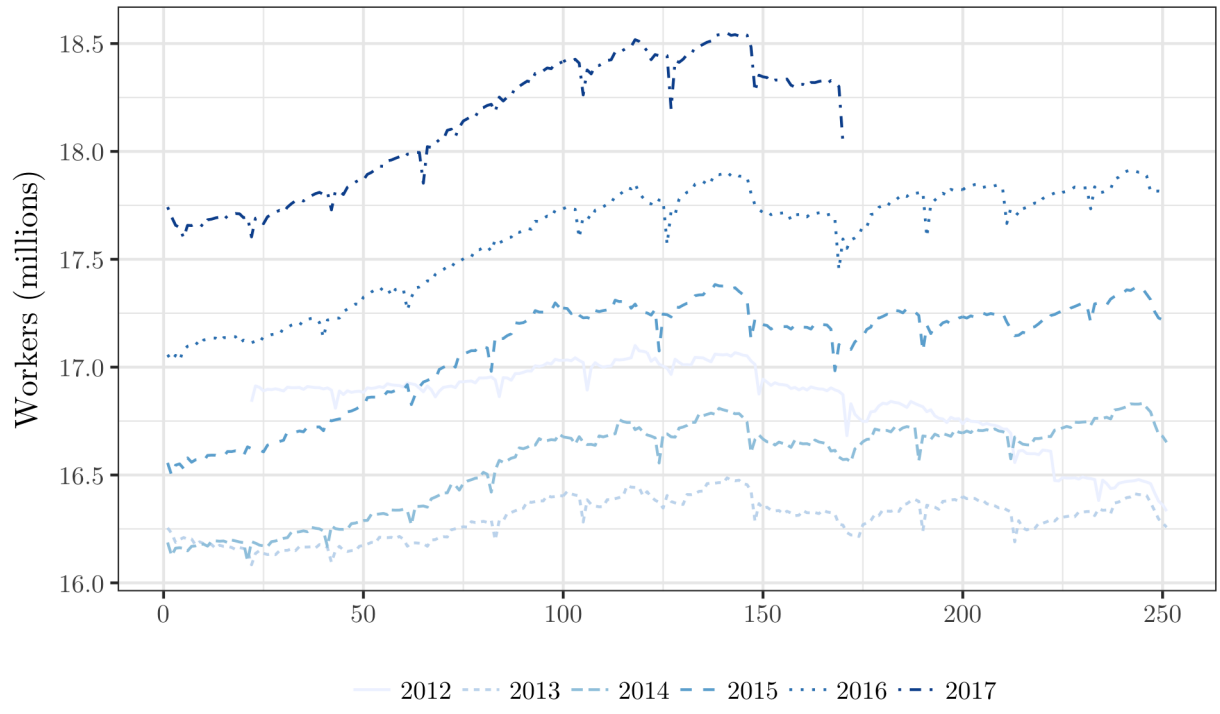
Next we provide a description of the data and the relative importance of the different calendar effects. Time variation and sectoral differences will be apparent from the description. We will go deeper into measurement afterwards.

2.1 The affiliation data

At first sight, the affiliation data exhibit clear yearly and monthly patterns. Figure 1(a) depicts the evolution of the daily register of Social Security affiliations in Spain from February 2012. The number of affiliations reached a minimum at the beginning of 2013 with 16,1 millions. After that, and starting by 2014, the picture shows a clear annual pattern of growth along a rising trend. The number of affiliates has increased by 13 per cent, to reach 18,3 millions (our last month), growing by 3.5 per cent annually (0,6 millions new affiliates per year). Moreover, every year along the expansion there is a steep rise in the first part of the year, which is then flattened along the second part.

[4]To make comparable the figures by occupations with the aggregate Social Security data, we have assigned the contracts registered during the weekends or bank holidays to the closer subsequent labour weekday.

(a) whole sample



(b) per years

Figure 1: Daily Social Security affiliates, 02/01/12 - 08/31/17.

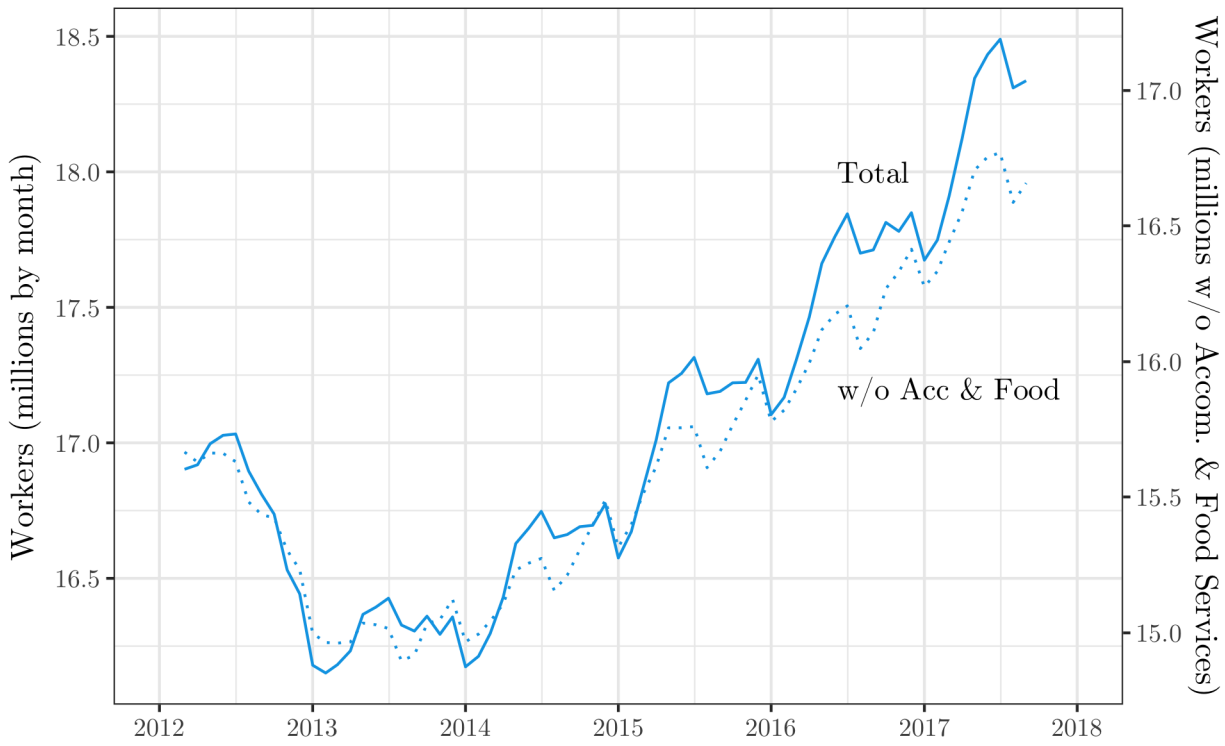
Figure 1(b) shows a comparison of the annual pattern across the years. Apart from the series for 2012 which is depicted in the middle of the graph. From 2013 to 2017 the data series are ordered upwards showing the increase in affiliations (expansion), and always exhibiting a clear "first up, then flat" pattern (within year cycle). In addition, it is apparent that there are recurrent fluctuations across months, with substantial drops that occur particularly by the end of some months. We would like to understand the drivers behind this time series pattern at the high frequency the daily registers provide. Our strategy will consist of pulling away the deterministic drivers from the stochastic components.

In particular, the ladder shape pattern in affiliation growth that we observe is highly related to seasonal economic activities. Figure 2(a) shows the affiliation data now on a monthly basis together with a series that subtract from it the accommodation and restaurant services activities. Clearly, along the expansion, affiliation in the food and accommodation sector first goes up and then down. This brings about the issue of the sectoral composition of the economy and its interaction with aggregate labour market fluctuations. This interaction operates through cross-sectional changes in the share of temporary workers at some particular activities as Figure 2(b) illustrates.

2.2 The flow data: creation, destruction and new contracts

Figure 3 summarises the path of employment creation and destruction across the six years in the sample. For comparison purposes we include the aggregate number of new contracts, all figures are in millions. The behaviour of the series deserves various considerations. The bigger spike corresponds to the beginning of every week, normally a Monday except if a holiday, so we will refer to this spike as a *Monday effect*. There is also a spike by the end of the week, and we will refer to this as a *Friday effect*. The Friday effect is less important than the Monday effect though. in addition, the Monday effect is one in which both creation and destruction of jobs coincide, except if the first day of the month is different from a Monday. Actually, the spikes are bigger if the beginning of the week coincides with the beginning of the month, and correspondingly, if the end of the week coincides with the end of the month.[5] Also, the spikes are typically larger during the summer period, and the effect turns out to be stronger the more the economy moves along the expansion period of the

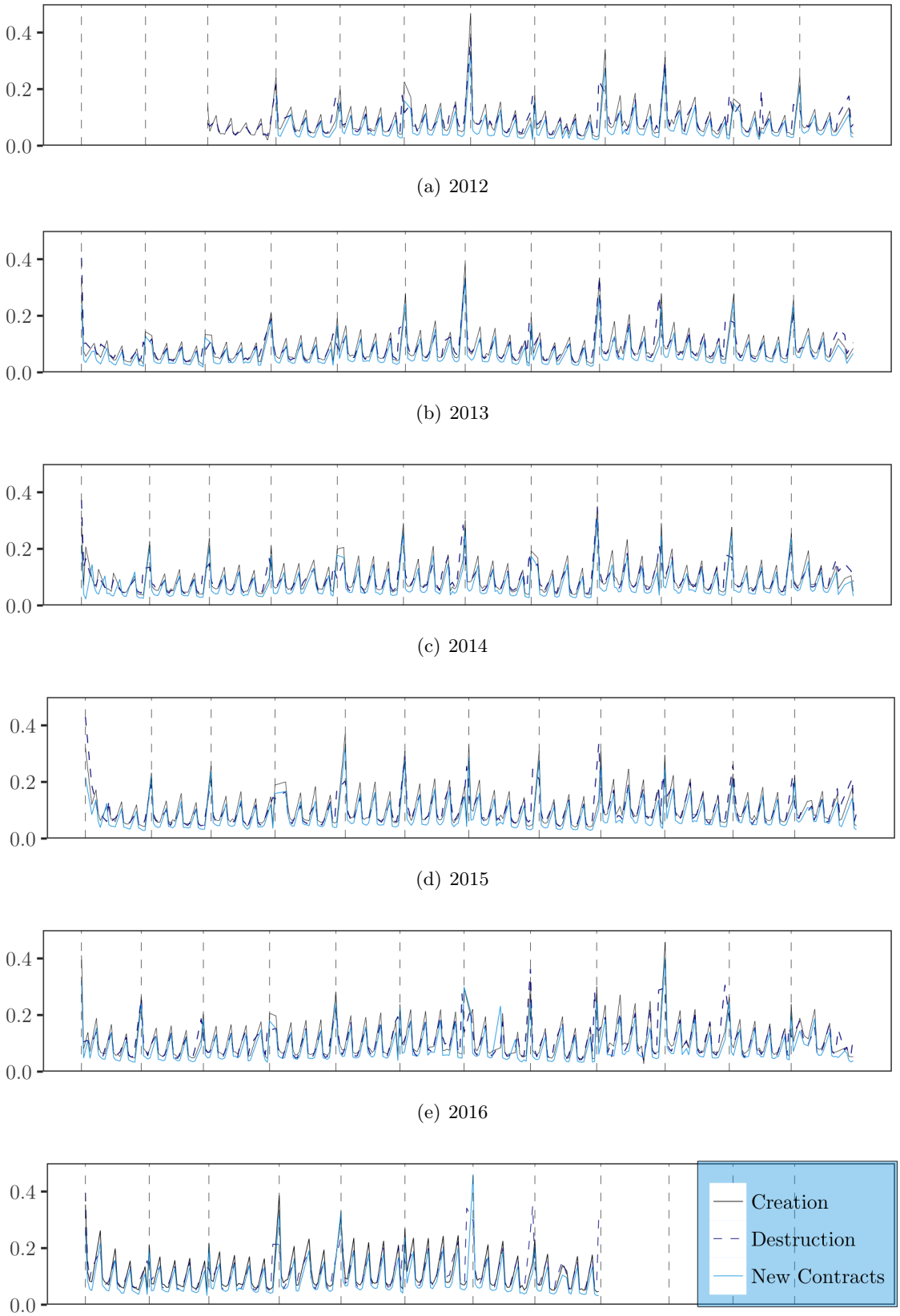
[5]Table A.3 in the appendix records this effect when the end of the month coincides with the end of the week (the highest spike on employment destruction occurs) and when the start of the week coincides with the start of the month (the highest spike on employment creation occurs). Notice that the employment spells that are destroyed or created each month are approximately a 10 per cent of total affiliates, a monthly rate similar to the annual rates for the US.



(a) Soc Sec affiliates (**monthly averages**): aggregate and excluded restaurant and accommodation services

(b) Temporary employment rate (fixed-term i/total sector i): aggregate and selected sectors. Source EPA

Figure 2: Employment measures in various sectoral activities



(a) 2012

(b) 2013

(c) 2014

(d) 2015

(e) 2016

(f) 2017

Figure 3: Creation and destruction, together with new contracts (all in **millions**) over the years (vertical lines go first workday each month).

business cycle. A detailed explanation of the data is given in Appendixes A and C.

In Section 3 we quantify the importance of these spikes with regression techniques, and we elaborate on the economics behind them. Clearly, individuals and firms coordinate their activities or decisions according to the calendar. For instance, individuals receive the wage pay at the end of the month or firms start a new campaign at the beginning of a year, etc. Therefore, it is not surprising to expect some calendar regularities or patterns within our daily series. Moreover, as we mentioned above, Monday becomes a crucial day because, in our daily series, all the employment creation and destruction that occurs over the weekend is recorded at the beginning of the workweek. Consequently, part of the Monday effect relates to a distortion associated to the unregister that occurs over the weekend.

2.3 Preliminary evidence on the determinants of the calendar effects

All the aforementioned patterns of the data can be understood from some basic determinants, somewhat discussed in the Spanish labour market literature with lower frequency data. First, as we mentioned in the introduction, the main characteristic of a dual labour market, as it is the Spanish one, is the coexistence of fixed-term contracts with low firing costs and permanent contracts with high firing costs. This institutional rigidity of the Spanish labour market gives rise to firms that want to avoid a permanent labour relationship. The excessive use of fixed-term contracts, as the default option for new contracts, creates the high volatility in the labour market we observe. Measuring calendar effects is useful to learn about varying volatility of employment over the business cycle.

Secondly, temporary contracts can be made for a very different duration, from hours to days, weeks, months or even years. In principle, companies can use this flexible menu of contracts to adapt to their production needs. However, when firms use this menu to avoid social security contributions and the implicit salaries embodied to holidays, or even to cash workers' unemployment benefits, it is not surprising that fixed-term contracts go beyond production needs or cyclical adjustments. Indeed, an administrative inspection of these practices might help, but in the end, temporary contracts are being used to avoid any risks, up to small changes in demand. All these circumstances explain why firms heavily rely on very short time contracts, shorter than a month, like week contracts or even weekend or bank holiday contracts. Compared to idiosyncratic risks, the analysis of high-frequency data may give a measure of the importance of administrative frictions, bureaucracy or fraud.

Thirdly, while the two main points above are crucial, we can not overlook that there are two sectors that concentrate the bulk of creation and destruction every day. These are tourism and agriculture. The temporary employment rate of both sectors is really high (see again, Figure 2(b)), about 60% and 40%, respectively. This confirms in particular the strong seasonality of job creation and destruction, along the late spring and complete summer periods for tourism, and through the fall term for agriculture, that we are tracking with sectoral data. Further, different months are different, and how different they are is made apparent only by measurement with daily data.

Last but not least, the monthly data reported are obtained from daily registers that are poorly treated: *i)* as indicated above, the register skips contracts signed during the weekends and holidays; *ii)* register chooses the date of social security affiliation automatically according to the queue of entry of contracts (this may coincide or not with the beginning of the contract); *iii)* the rule is that once the register does not correspond to a workday, it is imputed to the workday immediately after. Thus, the register in any workday after a holiday is distorted and this is particularly so every Monday, and to a larger extent if the holiday is by the end of the month.[6] Data issues are then a must too.

All these distortions amplify the spikes of temporary employment in Spain, either driving the hiring and firing decisions of firms or by introducing noise in the register. These circumstances apart from having deep consequences for workers and firms, make the use of either the average monthly data or the end of month figure problematic for time series purposes or to nowcast activity. As a consequence, we argue that organizing the aggregate evidence by looking at the daily registers is of particular importance, and key for the design of policy recommendations. In the following sections we try to disentangle all these different elements.

3 Calendar effects in daily job creation and destruction

In Section 2.2 we described the daily patterns of employment creation and destruction, as well as the related evolution of new contracts. In particular, Figure 3 above illustrated that employment flows concentrate on Monday and Friday, except when these days are different from the beginning or the end of the month, respectively. At the same time, creation and destruction are reinforced

[6] It is worth noting that the MESS (Ministerio de Empleo y Seguridad Social) calculates monthly averages without taking into account the weekends and holidays. Our joint analysis of social security and new contracts registers reveals that our findings go well beyond poor data collection though.

when the beginning or end of the week coincide with the beginning or end of the month. Aggregate new contracts and job creation move alike except for smoothing associated to movements in the self-employed, whose figures go up when new hirings moderate. Next we identify the extent to which measured calendar effects go beyond visual inspection.

3.1 A time series model for daily employment flows

We specify a deterministic and autoregressive time-series model in logs for all our flow variables of interest,

$$\log\left(\text{flow}_t\right) = \beta_0 + G\left(\xi_t^n; \beta\right) + m_t, \tag{3.1}$$

where the "flow" variable can be job creation, job destruction, or the register of contracts, and ξ_t is a set of dummy variables up to order n for calendar effects, so that β is a $(N \times 1)$ vector of regression coefficients. Finally, the error term m_t is allowed to follow an ARMA model

$$m_t = \frac{\sum_{j=1}^{J} \theta_j \, B^j}{\left(1 - \sum_{k=1}^{K} \varphi_k \, B^k\right)} \varepsilon_t, \tag{3.2}$$

with $B^{j,k}$ being the lag operator of order j or k correspondingly, and $\varepsilon_t \sim \mathrm{N}(0, \sigma_\varepsilon^2)$.

The way we specify calendar effects is comprehensive to cover all possibilities. This amounts to include all daily and monthly effects, as well as their interactions. It turns out, however, that a compact representation comes to settle quickly with the descriptive evidence discussed above. For instance, it is the case that only the Monday and Friday (mildly) effects are significantly different from the rest of the workweek. Thus, to cover the direct daily effects, we specify the constant β_0 in equation (3.1), together with the Monday and Friday dummies. Likewise, only the effect of some months is significantly different from the rest, and in those cases, significance is associated to seasonal economic activity. Therefore, for the monthly effects, rather than specifying all possible interactions, we incorporate a set of seasonal dummies. These dummies account for economic activity during *i)* the summer season (an April to July dummy denoted `Sun`), *ii)* the agricultural season (a September-October dummy `Agri`, related to the harvesting of wine grapes), and *iii)* the Cristmas period (a December dummy `Xmas`). While these are the more salient cases of combined calendar effects, there are some other that we discuss below. In any case, an extended specification

of equation (3.1) along these lines is in Appendix B.

Table 1 summarizes our preferred specification among several equivalent. The left panel involves calendar time dummies and autoregressive elements, whereas the right panel includes the dummy variables related with the yearly seasonal cycle of economic activity in the Spanish economy. The table goes in three blocks, with the middle block summarized in Figs. 4(a) to 4(f). This middle block refers to the differential daily effect at the beginning and the end of the month for each and every month. Summary statistics go at the end of the last block. It is shown for the log of creation specification the adjusted R^2 is above 0.86 whereas it is above 0.77 for destruction, with the contribution of economic effects (seasonal dummies) to the regression fit being small. Also in the last block, the autoregressive estimates show that the pattern of persistence is strong at lags 1 (a day), and 19, 20 and 22 (a month), but not below so we skip intra-month profiles. Rather, lags 5 (one week) and 10 (two weeks) are significant only for the log of destruction. Beyond the finding at lag 5 and 10, there is an event specific dummy (DUM 202) that is significant only for job destruction: this captures job destruction the day after the general strike November 14th, 2012. Finally, controlling the regression for the economic activity dummies in general amplifies the calendar effects, and it interacts with the beginning and end of month effects as we will see below.

3.2 Key calendar effects

The key calendar results are twofold. First, it is clear the importance of the Monday effect both in job creation and destruction. Note that the Monday effect comes in the regression in three parts: *i)* in a dummy that takes value one every monday, that is, the direct MON(day) Effect, *ii)* in a different dummy that takes value one when the beginning of a month is a Monday (MON Beg of Mth), and *iii)* in a third dummy that takes value one the beginning of every month (Beg of Mth), if eventually it is a Monday. Thus, for instance, the negative sign in the coefficient of the dummy MON Beg of Mth in Table 1 is interpreted through this composition first, and in addition, under the key fact that all months are not alike as discussed below.[7] Likewise, the Friday effect combines the effect of the set of dummies that correspond to *i)* Friday, *ii)* Friday and end of month, and *iii)* end of every month if Friday. As expected, the direct Monday effect is more important for creation than for destruction, but strikingly the effect is not that different. Correspondingly, the Friday effect is

[7] Actually, the coefficient of the dummy MON Beg of Mth is positive in the regression that excludes a beginning of month dummy for every month.

Table 1: The univariate time series model for employment creation and destruction, together with contracts creation, without and with dummies for seasonal economic (econ) activity.

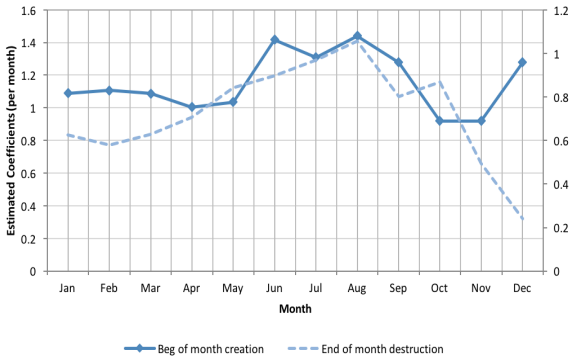
	Regression specifications					
				with seasonal dummies		
Variable	employment creation	contracts creation	employment destruction	employment creation econ	contracts creation econ	employment destruction econ
constant	11.057***	10.708***	11.079***	10.952***	10.631***	11.009***
	(0.035122)	(0.05617)	(0.071904)	(0.07284)	(0.12043)	(0.1059)
MON Effect	0.87515***	1.0189***	0.66191***	0.86902***	1.0012***	0.66626***
	(0.014255)	(0.011651)	(0.019427)	(0.014541)	(0.01191)	(0.019448)
MON Beg of Mth	-0.53674***	-0.66789***	-0.11658***	-0.54959***	-0.6942***	-0.12333***
	(0.050592)	(0.036903)	(0.047382)	(0.052484)	(0.036014)	(0.048867)
FRI Effect	0.023613**	0.006380	0.16743***	0.026592	0.0087621	0.17068***
	(0.014076)	(0.011949)	(0.01985)	(0.014568)	(0.012695)	(0.019557)
FRI End of Mth	0.091681**	0.13883***	-0.34755***	0.10342***	0.15177***	-0.35681***
	(0.058173)	(0.048783)	(0.042823)	(0.068396)	(0.054016)	(0.041774)
Beg of Mth all Mths	***	***	***	***	***	***
	SEE Figs 4(a) to 4(f) next page					
End of Mth all Mths	***	***	***	***	***	***

[cont after Figs 4(a) to 4(f)...]

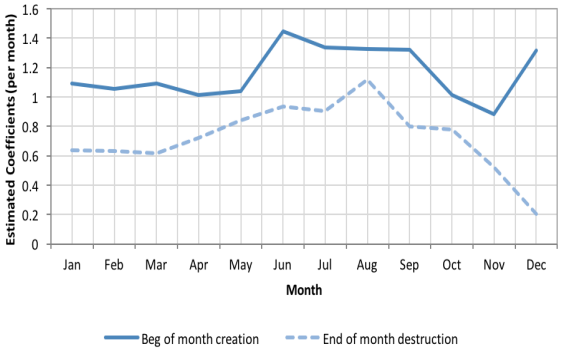
standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

more important for destruction than for creation indeed, but overall, as a calendar effect, it turns out to be a a lot less important than the Monday effect.

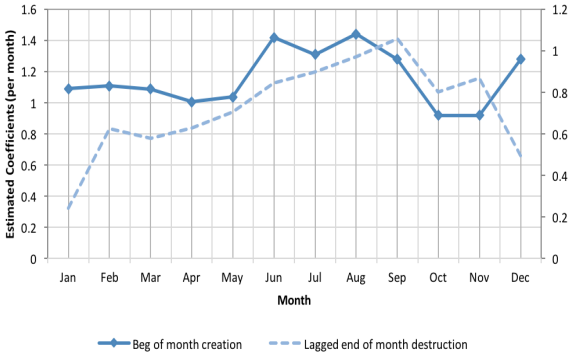
It is important to note that calendar effects are stronger for the flow of contracts than for the flow of employed and self-employed workers together (total employment creation). This occurs in all of the cases except for the direct Friday effect. Columns under "contracts" in Table 1 report this result, which is consistent with the finding in Carrasco (1999) that self-employment provides an escape to precarious workers, making them more attractive in terms of the labour cost borne by the firms. Further, the Friday effect difference between job creation and contracts suggests a weekly margin more associated to self-employed, whereas the monthly margin is more related to contracts. Finally, notice that the effect of paradoxical combinations Friday-and-beginning of month or Monday-and-end of month are non-significant. This reinforces the role of the coincidence of weekly and monthly starts and ends for employment dynamics in a fixed-term contracts environment as the one in Spain.



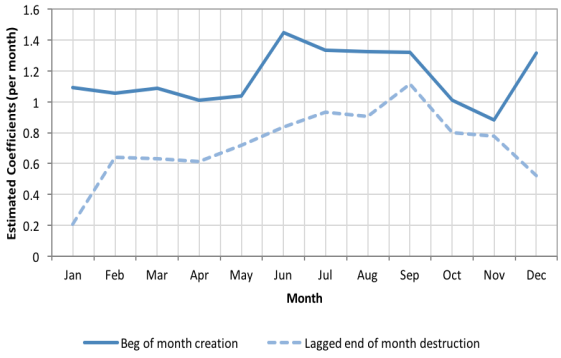
(a) Beg./End of Month Crea/Dest



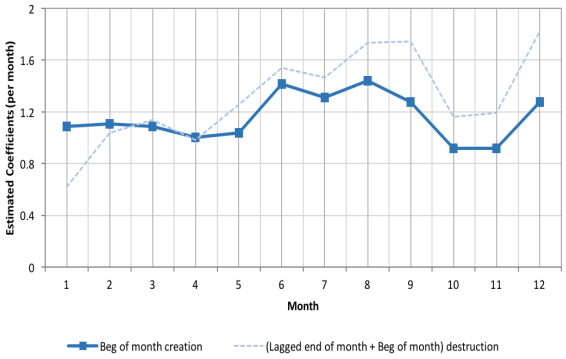
(b) Beg./End of Mth Crea/Dest with Economic Vars.



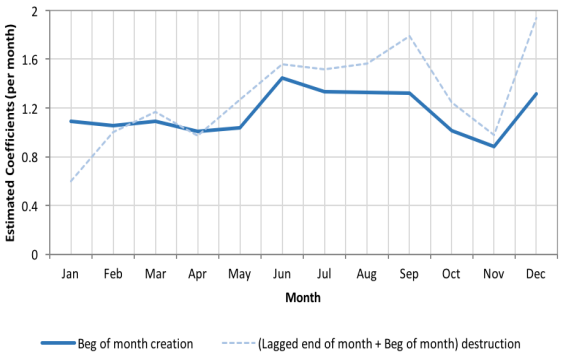
(c) Beg./Lagged End of Month Crea/Dest



(d) Beg./Lagged End of Mth Crea/Dest w/ Econ. Vars.



(e) (Lagged End+Beg.)/Beg. of Month Crea/Dest



(f) (Lagged End+Beg.)/Beg. of Mth Crea/Dest w/ Econ.Vars.

Figure 4: Estimated Beg/End of month patterns in job creation and destruction.

[...cont] The univariate time series model for employment creation and destruction, together with contracts creation, without and with dummies for seasonal economic (econ) activity. .

	Regression specifications					
				with seasonal dummies		
Variable	employment creation	contracts creation	employment destruction	employment creation econ	contracts creation econ	employment destruction econ
[...cont]						
DUM 202	0.015937	0.041035	0.72627***	0.04982	0.13706	0.72456***
	(0.09333)	(0.0558769)	(0.053799)	(0.075707)	(0.047094)	(0.045275)
Season Xmas				0.11747***	0.13965***	0.1562***
				(0.025247)	(0.019968)	(0.025423)
Season Sun				0.15354***	0.15064***	0.10577***
				(0.035907)	(0.029916)	(0.03398)
Season Agri				0.25344***	0.22194***	0.22398***
				(0.029751)	(0.025096)	(0.026128)
ar(1)	0.9827***	0.94682***	0.42352***	0.59588***	0.33504***	0.28577***
	(0.025289)	(0.031064)	(0.051479)	(0.052147)	(0.053664)	(0.063099)
ar(5)	-0.019117	0.00097635	0.15118***	0.11803	0.17785	0.14578***
	(0.018258)	(0.023876)	(0.023894)	(0.015916)	(0.023151)	(0.024295)
ar(10)	-0.033465***	-0.013563	0.073771***	-0.030587***	0.053028***	0.08086***
	(0.010987)	(0.013255)	(0.023591)	(0.016341)	(0.023978)	(0.024438)
ar(19)	0.10993***	0.064441***	0.1303***	0.1009***	0.06068***	0.15377***
	(0.030304)	(0.029046)	(0.028504)	(0.029216)	(0.028841)	(0.026715)
ar(20)	0.11961***	0.14258***	0.13455***	0.13128***	0.13128***	0.16811***
	(0.041205)	(0.040151)	0.031556)	(0.035601)	(0.030539)	(0.030629)
ar(21)	-0.0036971*	0.056982***	-0.038041*	0.06955***	0.143***	0.021867
	(0.044682)	(0.039768)	(0.032829)	(0.040679)	(0.031628)	(0.034224)
ar(22)	-0.19905***	-0.23154**	0.040267**	-0.038904***	0.052372***	0.084484***
	(0.030857)	(0.026712)	(0.025799)	(0.033985)	(0.031923)	(0.026638)
ma(1)	-0.73586***	-0.6489***	-0.056396	-0.3052***	0.090571***	0.01738
	(0.035422)	(0.046678)	(0.052826)	(0.057246)	(0.053408)	(0.064108)
Adjusted R-squared	0.86713	091668	0.77412	0.87058	0.92167	0.78714
F-statistic	240.7	405.1	126.87	248.07	433.18	136.832

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

The finding that calendar effects are amplified once we control for seasonal economic activity suggests episodic movements are important in non seasonal occupations too.

The second set of key calendar results (under rows Beg and End of Mth all Mths) has to do with rolling-over contracts. The beginning of each month is the starting date for the contracts with an employment duration of a month, and the end of each month is the termination date for those contracts. Therefore, we should expect a spike on the employment creation at the beginning of the month and a spike on employment destruction at the end of the month. Thus, we control in the regressions for the daily effect of the start or end of the month, and we do so with a different dummy variable in each case (beginning or end) every month. Then we proceed with a detailed analysis of the yearly cycle dimension of the estimated coefficients in Figure 4. We restrict to employment creation and destruction since the monthly calendar effects in contracts are not significantly different.

Fig. 4(a) put together the estimates (two scales) for the responses in creation at the beginning of the month and destruction at the end of the month. This comparison is therefore within the month: the effect on creation by the beginning of the month and on destruction by the end of the same month. Notice from Fig. 4(b) that once we control for the seasonal economic activity the estimates are not that different in size, and actually, the gap in the figure should give a measure of average net employment creation along the year. This gap widens indeed at the beginning of the year, employment creation indeed, and narrows during the summer, with the beginning of June spike on creation nearly compensated with the spike by the end of august in destruction. The main calendar discrepancy occurs in firing by the end of November and December, related with the Christmas season.[8] This motivates the concatenation of creation and destruction depicted in Figs. 4(c) and 4(d), that summarise the response in creation at the beginning of the month together with the response of destruction at the end of the previous month. Except for January vs. December, as the year goes by, the more the destruction at the end of the month corresponds to creation beginning next month. Moreover, the last panel, Figs. 4(e) and 4(f), put together the destruction estimates: lagged and contemporaneous destruction, together with every beginning of month creation. The estimated coefficients move together and often exactly cancel out.

We conclude that there is a lot to learn from the calendar movements in job creation and destruction associated to the prevalence of fixed-term contracts. Possibly, a break in this tight link

[8]Note the effect is not mitigated once we include the Christmas dummy in the regression as depicted in Fig. 4(b). This is not surprising as far as in the aggregate the holidays and activity effects during Christmas compensate.

over the calendar year would give a measure of the effectiveness of any policy designed to mitigate the prevalence of temporary contracts. The question is whether misuse of calendar margins in the flexibility of contracts might affect the way firms internalize employment protection legislation, and determine in part the bulimic (huge job creation and destruction) labor market in Spain. Next we provide some evidence of the consequences for employment dynamics of the calendar margins that have been just identified.

4 Aggregate employment dynamics over the calendar year

Our goal is to analyze the role of calendar regularities on job creation and job destruction, but why should we care? One obvious measure of the importance of calendar effects is whether they reflect into net employment creation. In this section we explore the transmission of calendar effects to the stock of Social Security affiliates. We find that affiliation growth is a lot governed by calendar regularities, and what it is more important, that every end of a month occurs a systematic fall in the stock of affiliates. To evaluate this asymmetry we propose a Markov Switching model for the growth rate of the number of affiliates. Under this model, and once controlled by calendar effects, we identify a regime switch between a "normal" state most of the time, and a state of low growth by the end of every month. Such a regime switch is more intense during the second part of the year and the more the economy moves into the expansion phase of the business cycle. We consider these are very important findings that should help to account for aggregate labour market fluctuations in Spain. In particular, the identified business cycle asymmetry affects employment dynamics and make the use of monthly data problematic for time series purposes or to nowcast activity.

4.1 A time series model with regime switching for employment growth

Let us consider the number of affiliations in Social Security, affi_t, on a daily basis. In line with the discussion in Section 3 above we specify an univariate time series model now in first differences,

$$\bigtriangledown \log\left(\text{affi}_t\right) = F\left(\bigtriangledown \xi_t^l; \beta\right) + a_t, \tag{4.1}$$

with $\bigtriangledown$ being the first-difference operator, ξ_t a set of dummy variables up to order l in first-differences (so $l \neq n$ above), and the error term a_t is allowed to follow an ARMA model

$$a_t = \frac{\sum_{j=1}^{J} \theta_j \, B^j}{\left(1 - \sum_{k=1}^{K} \varphi_k \, B^k\right)} \varepsilon_t,$$

with $B^{j,k}$ being the lag operator of order j, k and $\varepsilon_t \sim \mathrm{N}(0, \sigma_\varepsilon^2)$. Notice that under linear $F(\cdot)$ the specification in (4.1) is equivalent to a specification in levels such as

$$\log\left(\mathrm{affi}_t\right) = F\left(\xi_t^l; \beta\right) + b_t, \quad \text{with } b_t = \frac{a_t}{1 - B},$$

so that the β parameters will have direct interpretations on affi_t as we discuss in Section 4.2 below. Note that model (4.1) incorporates all deterministic and autoregressive elements identified before for employment flows, provided they are significant for the movements in the growth rate of affiliations. In particular, the empirical model provides a measure of the incidence of the substantial drops that occur by the end of some months as discussed above, now in the form of a regime switch. For this purpose, let us call variable det_t the right-hand side in equation (4.1), that is $\bigtriangledown \widehat{\log\left(\mathrm{affi}_t\right)}$, where the hat denotes 'predicted". We estimate a Markov Switching model for the residuals of the time series model, that is,

$$\bigtriangledown \log\left(\mathrm{affi}_t\right) - \mathrm{det}_t = \mu_{s_t} + \nu_t, \tag{4.2}$$

where $\nu_t \sim \mathrm{N}(0, \sigma_\nu^2)$ is assumed to be white noise, and two states $S_t = \{1, 2\}$, with transition probabilities $\Pr(S_t = h | S_t = h) = p_{hh}$ and $\Pr(S_t = i | S_t = h) = 1 - p_{hh} = p_{hi}$.

4.2 The incidence of calendar effects on employment growth

Table 2 summarizes the estimates of the time series model for affiliation growth. Although very stylized, the deterministic model accounts for about 70 per cent of variability. The autoregressive components are significant at monthly lags, but not particularly so below 20 to 23 days. Thus, we skip intra-month persistence profiles. There is again, now D(ifferenced), DUM 202 to capture the negative affiliation growth the day after the general strike November 14th, 2012.

As expected, daily mean growth is not significantly different from zero. However, and with

Table 2: The univariate time series model for the growth rate of affiliations. We include differenced dummies consistent with the model for the flows: D DAY Effect,

Variable	Coefficient
constant	5.08E-05
	(5.96E-05)
D MON Effect	0.000449***
	(6.11E-05)
D MON Beg of Mth	-0.00091***
	(0.000188)
D FRI Effect	-0.000475***
	(5.89E-05)
D End of Mth all Mths	SEE Fig 5 ***
	(next page)
D Season Xmas	-0.001973***
	(0.000366)
D Season Sun	0.00437***
	(0.000552)
D Mth January	-0.002404***
	(0.000527)
D Mth March	-0.002318***
	(0.000622)
D Mth April	-0.001876***
	(0.000518)
D Mth June	-0.001058***
	(0.000395)
D Mth September	-0.001539***
	(0.000423)
D Mth December	0.003371***
	(0.00054)
AR(1, 10)	negative ***
AR(19, 20, 21, 22, 23)	positive ***
Adjusted R-squared	0.706145
S.E. of regression	0.001158
Schwarz criterion	-10.5346
Log likelihood	7382.925

respect to economic activity, the summer season is estimated on average 0.4% per cent above mean growth. Rather, the holiday effect during Christmas dominates the activity effect, so affiliations growth is 0.2 per cent below. On the other hand, with respect to calendar effects, we find that affiliation growth on Monday is positive, whereas the effect on Friday is negative and nearly the same size. This suggests an important fluctuation within the week, possibly capturing the strong incentive for firms to avoid the extra salaries and social security contributions associated to the weekends. Moreover, Monday and beginning of month is also significant and its effect on affiliation growth doubles the one of the average Monday, but with a negative sign. As before, this is the composition of Monday effects, but now notice that in first-differences we can only handle one in every two consecutive dummy variables, so here we skip the Friday end of month effect. However, as highlighted next, we select the end of month every month effect, which is the key calendar issue.

Indeed, without a doubt, the key deterministic effect on the growth rate of affiliations is the destruction of contracts by the end of every month. To capture this effect we include a dummy per month that reflects the end of month effect: D(DUM) <Month> L(ast)D(ay)). This effect turns out to be significant (except December) and always negative but different in magnitude for each and every month. Actually, the effect is significantly higher from March to August, and reflects that the probability that affiliations are destroyed by the end of the month is higher as time goes by across the calendar year.[9] Figure 5 reports these estimates with a marked calendar effect along the year.

This key finding motivates the focus on the regime switching model for employment dynamics. Table 3 reports the estimation results for the Markov-Switching model. The table shows a change of mean that is significant between two regimes: a "normal" state most of the time, and a state of low growth by the end of every month. Remember that estimates refer to the mean of the residuals of the growth rate in affiliations once we control for calendar effects and autoregressive components. Then, Regime 1 captures the residuals of the time series model by the end of each and every month. This regime has an estimated mean of -0.00384, a 0.384 per cent below average, whereas the mean of the rest of observations is positive at 0.00021, so very close to zero. The transition probabilities between regimes are displayed in the bottom panel of the table. The persistence of Regime 1, the low growth state, is 0.0996, so very low, whereas the persistence of Regime 2 is 0.973, very high. Such a persistence of Regime 2 might suggest stability of employment growth within the month,

[9]The end of quarter effect is significant (but less), and negative, end of June and end of September, while positive end of March and end of December. The end of year effect is augmented with a positive beginning of year effect. In any case we will not elaborate further on these particular calendar effects.

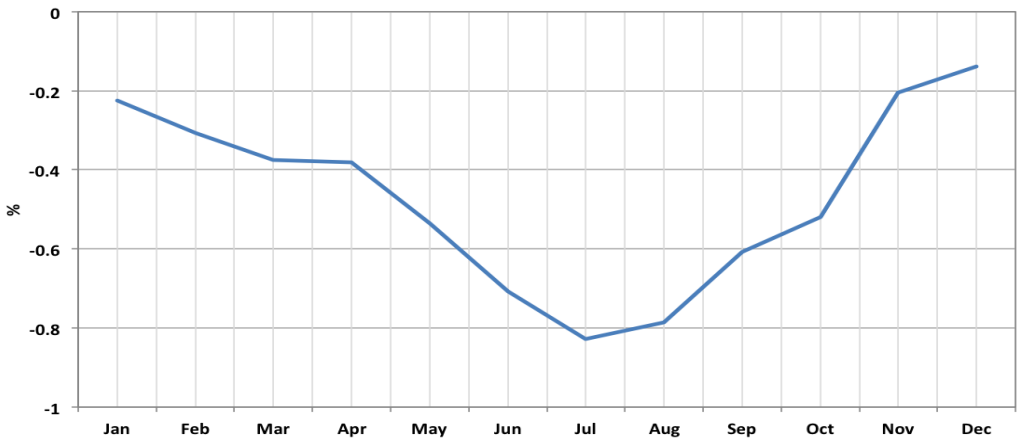


Figure 5: Estimated average "end of month effect" on affiliations growth, all months.

but it is only after we control from the Monday (key) and Friday (less important) effects.

This "calendar adjusted" employment growth stability (stationarity) is definitively lost over the business cycle according to the regime switches characterized by the Markov model. Figure 4.2 depicts the total number of affiliations (the raw daily time series), together with the probability of changes in the mean of the Markov-Switching model (the vertical solid lines). The grid depicts also (dashed) both the end of months and years. It is apparent that since the beginning of the expansion, circa 2015, the probabilities of regime change by the end of the month have increased. In fact the high probabilities concentrate in the second half of the year and reflect a more intense destruction of contracts by the end of the month after every May during the expansion period. This is consistent with the pattern observed in Fig. 2(a), and provides a measure of the prevalence of fixed-term contracts during the expansion. Moreover, our estimated persistence parameters imply average durations of 1.2 (Regime 1) and 36.9 days (Regime 2), respectively. That is, Regime 2 roughly corresponds to 2 months of weekdays, consistent with the fact that regime switches occur generally every year from May to October. In this sense, our estimated regime change probabilities are a measure of how strong is job creation by the Spanish productive model during economic booms. This can be related from a business cycle perspective with Camacho et al. (2017) finding that regions where economic activity mostly gravitates around the tourism sector, the Canary Islands and Valencia, followed by the Balearic Islands, lead the national business cycle peaks. However, from a labour perspective, the existence and duration of Regime 1, in its turn, may reflect a significant failure in employment legislation, or fraud, or both.

Table 3: The markov switching model

Variable	Coefficient	Std. Error	z-Static	Prob.
Regime 1				
α_1	-0.003838	0.000275	-13.96809	0.0000
Regime 2				
α_2	0.000211	2.83E-05	7.431043	0.0000
Common				
LOG(SIGMA)	-6.961807	0.021427	-324.9087	0.0000

Transition Matrix

		1	2
All periods	1	0.099632	0.900368
	2	0.027096	0.972904

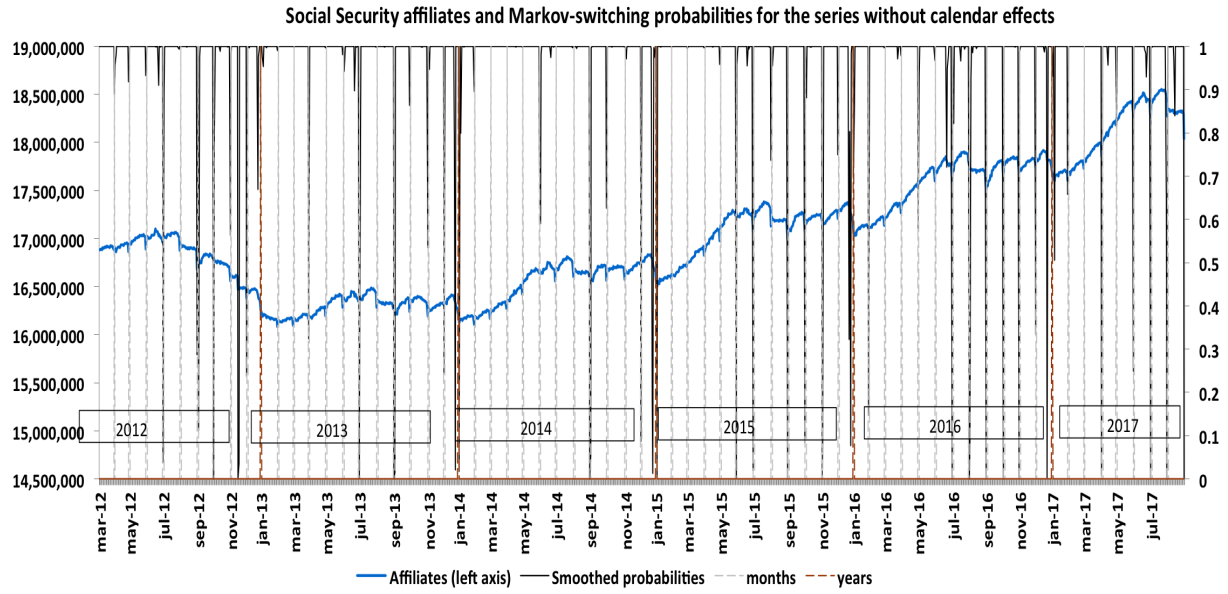


Figure 6: Number of daily Social Security affiliations, and estimated changes in the mean of affiliations growth, over the different years after calendar and autoregressive effects.

5 Sectoral composition and the calendar effects

This section investigates the determinants of the calendar effects we have identified. Among the alternative explanatory variables on a daily basis we might consider, we single out the effects of changes in the sectoral composition of new contracts registered in SEPE (Servicio Público de Empleo Estatal/Official Employment Information Administration).[10] In Section 3 we used the aggregate daily series of new contracts to replicate the calendar effects obtained for job creation. Here we exploit the occupational structure of contracts to learn about the strength and variability of calendar effects. Remember that all calendar effects measured on job creation are exacerbated if measured in new contracts (see Table 1). Remember also that we only paired job creation with new contracts because we just have information on the starting dates of contracts.

We select occupations because this way we observe workers with higher disaggregation. Regarding aggregate employment though, just remind our focus is on job creation rather than contracts in order to consider both employed and self-employed workers. First, we comment on the endogenous and explanatory variables. Then, we discuss our econometric specification. This involves primarily the construction of the calendar variables of interest and the identification of their comovements with new contracts in the different occupations. Next, to interpret these comovements, we further estimate calendar effects by occupations and we relate their strength with the figures for temporary employment in Spain. Finally, we look to the variation of calendar effects over time.

5.1 Occupational structure according to the registered contracts at SEPE

All new contracts in the universe of registers at SISPE (Sistema de Información de los Servicios Públicos de Empleo/Official Register of Employment) are coded at SEPE with an identifier for the different occupations. The classification of occupations follows roughly the International Standard Classification of Occupations (ISCO-88), and we report them in the Appendix. In any case, there are many occupations registered even at two digits so we select those with more volume of contracts across time. We choose occupations with *more than 1000 contracts a day* on average over the sample. With this selection we cover on average nearly 75 per cent of the new contracts every day.

[10] Alternative daily data if available, confronted with different measures of calendar effects, could give relevant information for the design of policies to mitigate the high incidence of temporary contracts. Clearly though, the possibility of considering alternative explanatory variables of the varying intensity of calendar effects is limited by the availability of data. Registers of foreign visitors or hostel accommodation on a a daily basis are good candidates.

With this set of explanatory variables our strategy is as follows. First, we regress the outcome variables, say measured aggregate monday and friday effects (remember, only job creation since just available starting dates), on the share of contracts for each sector-category of employment in the register. This shows that the strength of calendar effects is driven by key occupations. Then, we estimate occupational calendar effects and we relate them with the temporary rates of the corresponding occupations. This identifies high temporary rates of employment with occupations that display strong calendar effects. Finally, we run simple *threshold regressions* to identify variation over time. This suggests asymmetry in highly temporary occupations for which labour market policy should devote special attention.

5.2 The contribution of the different occupations to calendar effects

Aggregate calendar effects on employment creation are defined by the series of *filtered hirings* in logs, say $\widetilde{\text{hirings}}_t$.[11] We construct,

$$\widetilde{\text{hirings}}_t \equiv \text{hirings}_t - \widehat{\text{hirings}}_t + \hat{\beta}^{\text{ce}} \cdot \xi_t^{\text{ce}} \tag{5.1}$$

where $\text{hirings}_t - \widehat{\text{hirings}}_t$ are the residuals in regression (3.1), and $\hat{\beta}^{\text{ce}} \cdot \xi_t^{\text{ce}}$ is the estimated effect of the dummy variable ξ_t^{ce} in that regression, with "ce" being monday "me" or friday "fe" effects. We construct alternative *filtered variables* from the regressions with season and economic dummies.

In particular, remember that for the log of employment creation model (see Table 1), the $\hat{\beta}^{\text{me}}$ is about 0.875 (s.e.: 0.0143, 0.869 (0.0145) with economic effects), whereas the $\hat{\beta}^{\text{fe}}$ is only 0.0236 (s.e.: 0.014, 0.0266 (0.0146) respectively). Remember also that such a deterministic model explains more than 85% of the time series behaviour of the log of job creation. Therefore, when we exclude the monday effect for instance, we are above 70% explanatory power for daily job creation obtained from the rest of calendar and economic time dummies. The goal of our specification is first to compute linear correlations between the unexplained 30% contained in $\widetilde{\text{hirings}}_t$, call it stochastic part, and the daily creation of contracts in various occupations. Therefore, once we construct the filtered variable, $\widetilde{\text{hirings}}_t$, we regress it against the share of contracts every day in selected occupations

[11] Next we refer to "hirings" to stress the use of contracts as explanatory variables. Thus, our empirical approach here accounts for "employed" social security affiliates, and by the result in Section 3 on calendar effects' smoothing through self-employed, we provide a lower bound for the intensity in the comovement of occupations.

partialling out the corresponding calendar effect. That is,

$$\widetilde{\text{hirings}}_t = \gamma\, \xi_t^{\text{ce}} + \sum_{i=1}^{I} \delta_j s_{it} + \eta_t, \tag{5.2}$$

where ξ^{ce} is a dummy variable for the corresponding calendar effect, and s_{it} is the share of contracts in occupation i over the total of contracts in all of the $M > I$ selected occupations at each labour day t. We include controls for autoregressive parts, η_t, so as to account for any remaining structure associated to omitted occupations.

Positive correlations with the variability of job creation

Table 4 reports the estimated coefficients. We focus on sign and significance of the estimates. The reason is that even though coefficients are normalized (shares divided by its sector average), they are large for occupations with relatively small average share of contracts. We find that occupations positively correlated with the "monday effect" (Table 4, top panel) are C96 (untrained workers/elementary occupations in construction and mining) and C97 (untrained workers in manufacturing); C51 (restaurant services) and C52 (shop assistants); and C22 (teaching and educational professionals) together with C37 (cultural and sport Services) and C44 (leisure services). Clearly, these are among the elementary occupations (group 9, group 5), and thus, typically, under fixed-term contracts. Note that educational occupations involve teachers in primary, secondary and higher education, both technical and college based. Variability comes from the fact that the bulk of contracts in this particular sector goes at the beginning of each academic year (see Fig A.1(c) in Appendix A). This turns out to be enough to correlate positively with the variability of the beginning of workweek variable, and motivates in part our investigation of non-linear relationships below.

We could rank the contribution of these occupations to the variability of the Monday effect in various ways. Figure 7 summarises two simple proposals for the benchmark case under specification (1) in Table 4. The left panel considers a simple alternative based on dropping from the regression the positively correlated sectors, and then computing the joint adjusted-R^2 for the rest: it is 0.81 in the benchmark case. Then we compute the relative explanatory gain for each occupation, adding them one by one, as Fig. 7(a) reports. Proceeding this way, the gain with Manufacturing elementary and Restaurant Services is around 0.4 per cent each, whereas Educational alone represents a gain of more than 0.2 per cent. Sport and leisure services give a 0.3 per cent gain, but these are sectors

Table 4: Linear relations between daily share of contracts in the different occupations and variability of either monday or friday effect **in employment creation** (with or w/o economic dummies).

Variable		Regression specifications			
		Filtered Monday Effect	Filtered Monday Effect econ	Filtered Friday Effect	Filtered Friday Effect econ
constant				1.7984***	1.6554***
				(0.3187)	(0.3178)
Own effect		0.7164***	0.7215***	0.1034***	0.1265***
		(0.0221)	(0.0219)	(0.0263)	(0.0260)
occupations significant and **positively** related with variability of **monday** effect in creation					
Educational	C22	2.3443***	0.5614	0.6525	-2.3787***
		(0.6984)	(0.6944)	(0.8586)	(0.8571)
Cultural & Sport	C37	1.8902***	2.3437***	-0.7721	-0.0008
services		(0.4392)	(0.4361)	(0.6203)	(0.6203)
Leisure	C44	5.551***	5.4783***	0.7323	1.2783
services		(1.6749)	(1.6593)	(1.7852)	(1.7737)
Restaurant	C51	1.8045***	1.6244***	-1.6306***	-1.5260***
services		(0.3500)	(0.3472)	(0.4320)	(0.4297)
Shop	C52	1.9354***	1.3836*	-1.5434	-1.7983*
assistants		(0.3500)	(0.7488)	(0.9440)	(0.9484)
Construction	C96	3.3154***	3.0927***	0.7523	-1.4674
(elementary)		(0.8613)	(0.8494)	(0.9373)	(0.9261)
Manufacturing	C97	3.1963***	3.1993***	-0.5936	0.3456
(elementary)		(0.5544)	(0.5474)	(0.6991)	(0.6993)
occupations significant and **negatively** related with variability of **monday** in creation					
Artistic, Literary	C29	-2.6644***	-2.6505**	-3.1127***	-3.2129***
& cultural		(1.0151)	(1.0113)	(1.0035)	(1.0107)
Sellers	C54	-1.4388*	-1.3248*	-2.5975***	-2.7077***
out of shops		(0.8070)	(0.8001)	(0.9347)	(0.9302)
Construction	C71	-4.3996***	-3.7772***	-7.7936***	-6.6604***
(skilled)		(0.9451)	(0.9365)	(1.1180)	(1.1200)
Domestic	C91	-2.1960**	-1.6976*	-5.5494***	-5.5324***
cleaning		(1.0393)	(1.0371)	(1.0843)	(1.1152)
Food	C93	-10.9455***	-10.1531***	-3.5495*	-4.2911**
preparation		(2.2420)	(2.2165)	(1.9685)	(1.9702)
Shelf filers	C98	-14.4442***	-15.3502***	-11.7850***	-12.4295***
		(1.4533)	(1.4396)	(1.3819)	(1.3763)

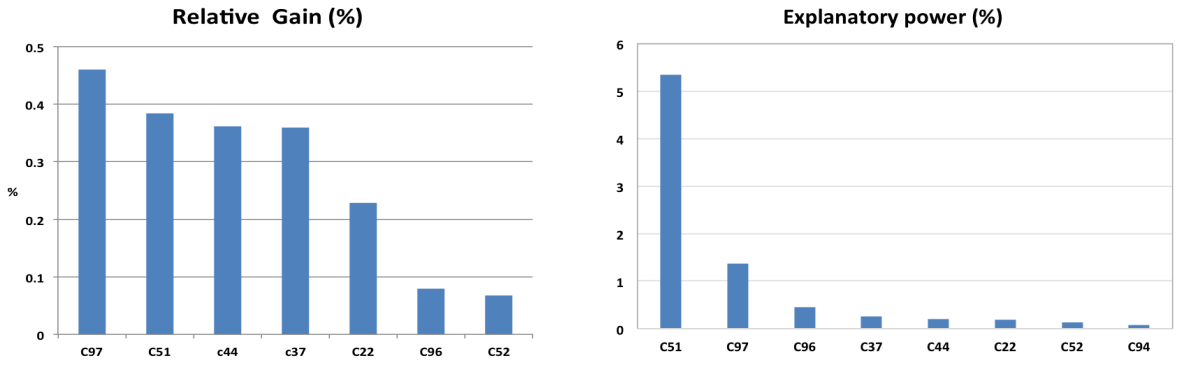
[cont...]

standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All non-significant C58-84-92-94.

[...cont] Linear relations between daily share of contracts in different occupations and variability of monday or friday effect **in employment creation** (w or w/o econ dummies).

Variable		Regression specifications			
		Filtered Monday Effect	Filtered Monday Effect econ	Filtered Friday Effect	Filtered Friday Effect econ
occupations significant for variability of **friday** effect in creation, always negatively related					
Health	C21	-1.4358	-1.4845	-3.4641***	-3.4220***
		(0.9450)	(0.9360)	(0.9898)	(0.9839)
Caring	C56	-0.8572	-0.6002	-7.1797***	-6.6716***
		(1.6042)	(1.5855)	(1.6924)	(1.6908)
Agricultural (elementary)	C95	0.1641	0.2008*	-1.6572***	-1.4674***
		(0.1130)	(0.1134)	(0.3555)	(0.3534)
AR(1, 20)				***, *	**, **
AR(5, 9, 22)		***	***	***	***
AR(7, 14)		**, ***	*, **	, ***	, **
Adjusted R-squared		0.833519	0.836452	0.199500	0.195163
S.E. of regression		0.166219	0.164258	0.166384	0.164346
Akaike info criterion		-0.7311781	-0.755516	-0.727602	-0.752246
Schwarz criterion		-0.630755	-0.654490	-0.614920	-0.639563
Log likelihood		515.5613	531.4399	515.7660	532.2552
Durbin-Watson stat.		2.019701	1.967448	2.010655	2.005060

standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All non-significant C58-84-92-94.



(a) Adjusted R^2 based measure

(b) Standardized $\hat{\delta}'s$ based measure

Figure 7: Ranking of explanatory power of the variability of the Monday effect for different occupations, 2012-17. Note units are per cent in both cases, but not comparable.

with a lot within variability (from sport coaches to travel agents). Finally, the gain by C52 and C96 is roughly at 0.1 per cent (low variability in Construction). Another ranking alternative is to approximate the adjusted linear simple regression, so we compute the standardized $\hat{\delta}$'s instead. Fig. 7(b) reports these numbers in percentage terms.[12] This sorting implies an overwhelming explanatory power for the restaurant services sector, now well above the elementary occupations in manufacturing. As indicated, the ranking differs from the one the size of the estimates provide. Our strategy here is to keep a simple methodological approach to illustrate the findings, but one may consider various counterfactuals for more elaborated policy purposes. Finally, there are small differences when we study the measured "monday effect" after controlling for seasonal dummies. Specification (2) in Table 4 shows, as expected, that most coefficients diminish, but not always. For instance, C95 (agricultural occupations) become significant once we control for seasonal patterns.

We interpret these findings as an evidence for occupations driving the variability (spikes) of episodic (monday) movements in hirings. At the same time however there are occupations comoving against the identified calendar effects as we discuss next.

Other correlations

The correlation of some occupations with the variability of episodic over-hiring can be negative instead. This just means that job creation in some sectors is negatively correlated with new contracts in the sectors that drive the monday effect. This occurs for instance with C91 (domestic cleaners), C93 (food preparation) and C98 (storage and shelf filers), as well as C54 (sellers out of shops and stores). Clearly, preparation activities in shops or food stores go before the sales. Likewise, domestic cleaners seem to show up when activity in the market cleaning sector declines. Thus, the reported evidence seems consistent with basic intuitions. Of particular interest is the tension between occupations C71 and C96: monday seems a bad day to bring plumbers, carpenters or glaziers to the building trade, but apparently it is the hiring day for all kinds of assistants to these.

We do not find evidence that the creation of contracts in occupations such C92 (cleaning) and C94 (elementary occupations in services), or C84 (urban and road transport drivers) is significant for the movements in the filtered, either monday or friday, variables. Alternatively, movements in occupations such C21 (health professionals, from doctors to therapists), C56 (caring), and C95

[12]The standardized $\hat{\delta}$'s are the estimated coefficients times the standard deviation of the regressor relative to that of the dependent variable. The square to this value approximates the $\hat{\delta}$ of the simple linear regression, and thus the percentage of variability explained by one regressor controlling for the other.

(elementary agricultural), are only significant for the friday effect on hiring, and again, with a negative sign. Indeed, all these occupations, apart from substantial within variance in some cases, do not seem to have such a clear pattern associated to the workweek as the occupations highlighted before, and clearly they do not seem "friday intense." More in general, specifications (3) and (4) in Table 4 report the corresponding correlations for the friday effect in hirings, and the more salient feature is that correlations across sectors are either negative or non significant. This may suggest that this sectors determine the variability of firing and not of hiring indeed. Notice that now, controlling for the economic activity tend to increase the estimated negative correlations.

Notice, in particular, that the restaurant services sector also exhibits a significant negative correlation with the variability of job creation on friday. Our interpretation is twofold. First, as contracts in restaurant services are found positively correlated with the monday effect, then it is the economic activity during the workweek, and not the leisure activity during the weekends, that drives contracts in this sector. Secondly, as contracts in restaurant services are negatively correlated with the friday effect in hirings, it is the case that friday hirings are relatively high when the share of contracts in the restaurant services occupations is low, which occurs mostly out of the summer time. Similarly occurs with the educational sector provided we control for overall seasonal activity: once friday effects are smoothed over the calendar year, and as far as the summer time, christmas, or the agricultural season, are not informative for hiring in this sector, the friday effect is strong when the educational sector is not hiring. This motivates the analysis of time variation of calendar effects over the year that we propose in subsection 5.4 below. Before, and even though the relevant question refers to the strength and time variation of aggregate calendar effects, one may wonder on the importance of calendar effects by occupations. We comment on this next.

5.3 Occupational calendar effects and temporary rates

Up to this point we have considered the aggregate calendar effects in employment creation. Now that we introduced the different series of new contracts by occupations as explanatory variables, we can consider the disaggregated calendar effects. In so doing, we implement exactly the calendar effects regression specified for the aggregates in equation (3.1) to each and every sector-category of employment at SEPE (results are available upon request). Then we collect the direct calendar effects $\hat{\beta}_i^{\text{ce}}$ for the $i = 1, ..., I$ selected occupations in the sample.

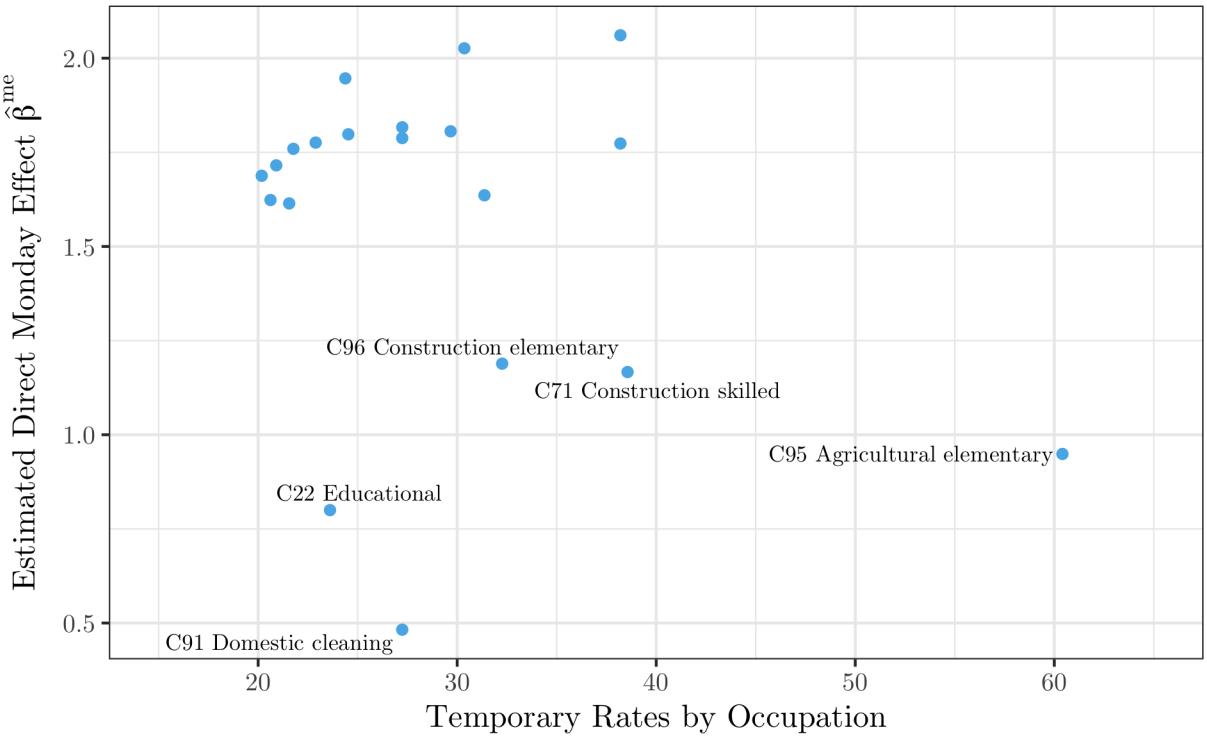
To summarize our findings, we relate calendar effects and the population of workers under fixed-term contracts in the different occupations. Figure 8 plots the scatter of the estimated coefficients for the direct monday effect in each occupation i, that is the $\hat{\beta}_i^{\text{me}}$'s, with their corresponding temporary rates computed as a weighted average of the temporary rates in the various sectors each occupation spreads. Figure 8(a) shows the scatter for all selected occupations. Monday effect is relatively strong for most occupations, as zoomed in Figure 8(b). The key finding is that occupations with stronger monday effects exhibit relatively high temporary rates. Note we fit to the scatter an order two polynomial with a 95% confidence interval. It worths to pay attention to the labels for the different occupations in Fig. 8(b). On the other hand, and back to Fig. 8(a), the few outliers ($\hat{\beta}^{\text{me}} < 1.2$) can be easily justified. For instance, we already showed (see Table 4, and discussion above) that agricultural and domestic cleaning occupations are not correlated with the aggregate monday effect, which is quite consistent with basic intuition. Also, educational sector is very special as it can be seen in Figure A.1(c). Finally, it is not surprising that considering the post housing boom period, as we do, explains why construction occupations are out from the north-east scatter.

Bearing in mind this cross-sectional evidence, both in the aggregate and disaggregated, we now turn to analyze the variation of calendar effects over time.

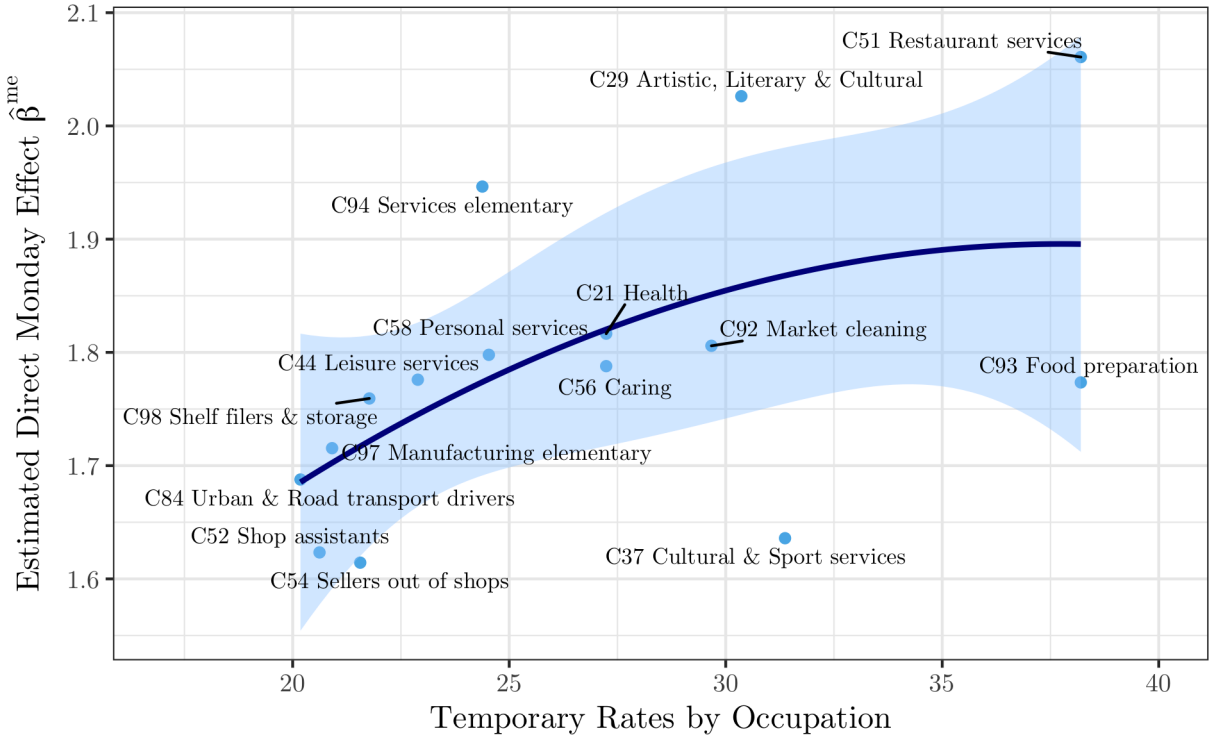
5.4 Time variation over the calendar year

Next we focus on variation of calendar effects over the calendar year. In so doing, we combine both the aggregate calendar effects and the information by occupations. We consider the following experiment. A naïve researcher, interested in episodic job creation flows, may want to compute the distribution of say, monday contracts, per month. A sophisticated researcher instead would rather take into account the variation in the intensity of calendar effects across time: a relative measure. We propose as a "candidate relative measure" the outcome of a threshold model for the filtered variable $\widetilde{\text{hirings}}_t$, where the threshold goes either "pro" or "counter" the corresponding calendar effect over time depending upon the occupation. This specification can be written as

$$\widetilde{\text{hirings}}_t = \alpha_{\text{pro}}\, \xi_t^{\text{ce}}\, \mathcal{I}_{\text{pro}} + \alpha_{\text{con}}\, \xi_t^{\text{ce}}\, \left(1 - \mathcal{I}_{\text{pro}}\right) + a_t, \tag{5.3}$$



(a) Selected occupations, all β's



(b) Selected occupations, selected β's

Figure 8: Average temporary rate and the direct monday effect by occupation, 2012-17.

where for each occupation the indicator function $\mathcal{I}_{\text{pro}}$ takes value one (zero otherwise) when

$$\frac{1}{J}\sum_{j=0}^{J-1} x_{t-j} > c, \tag{5.4}$$

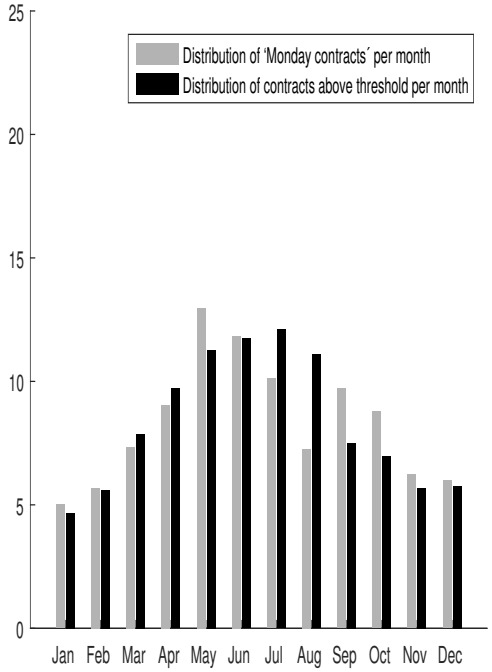
with $x_t = \sum_{i=1}^{P} c_{i,t}^{P}$, and $c_{i,t}$ being the fraction of contracts signed for activity-category i, $a_t \sim \text{N}(0, \sigma_a^2)$. J is an index of aggregation, that is, when $J = 1$ we do not average daily contracts but we could. Also, we could add up P different related occupations. The question is whether the calendar effect is explained more when hiring in occupation i is relatively high (say on "ce" day), and if so, how this is distributed by occupations along the calendar year.

We estimate the model for different c's in a grid $\left[c_{\min}, c_{\max}\right]$ and we choose the one that minimizes the variance of the regression residuals. We call such a c, the optimal threshold c^*. When the condition in (5.4) holds, it is the case that the calendar dummy explains with more intensity the filtered variable $\widetilde{\text{hirings}}_t$. The intensity of the threshold is given by parameter α_{pro}, and we test whether the parameter α_{pro} is significantly different from the parameter α_{con}. Subscript *pro* does not imply parameter α is greater than under *con*. It may indeed occur that the calendar effect is stronger in the complementary of condition (5.4), and therefore, more correlated with the filtered variable when the volume of contracts is below the threshold. Thus, we distinguish if a sector is *pro* or *counter* the threshold, and whether it is so with a *positive* or with a *negative* sign. We evaluate in an occupation the variation of the calendar effect over the year in the form of the fraction of contracts above the threshold.

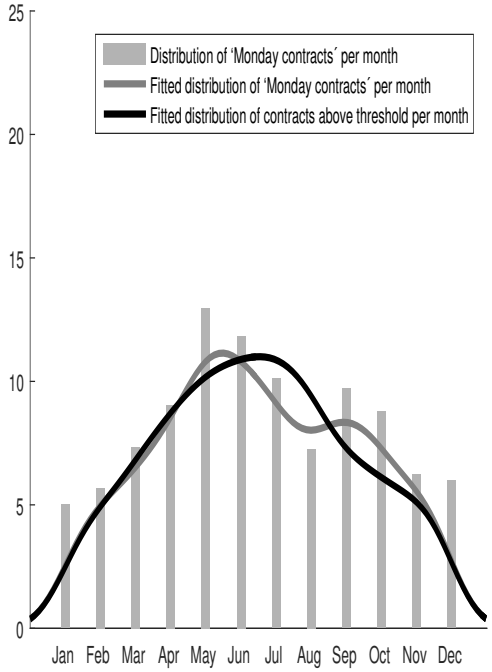
On the distribution of contracts over the calendar year

Figures 9 to 11 illustrate our findings. Let us take for instance the case of occupations in restaurant services (C51), summarized in Figures 9(a) and 9(d). The top panel [(a) and (b)] refers to the monday effect whereas the bottom panel [(c) and (d)] refers to the friday effect. The figures compare the "Raw" distribution with our relative measure of asymmetry: the "Tar measure." Remember that we found that this particular occupation was positively correlated with the *unexplained-by-calendar-but-for-the-monday-effect* part of hirings.

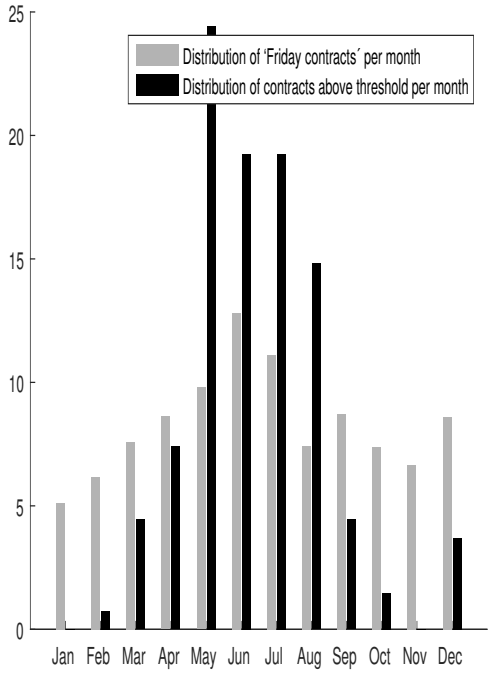
When we try to account for the *monday effect* with the threshold model, our estimates for this occupation identify a *pro monday effect* regime ($\alpha_{pro} = 0.92$) which is statistically different from the counter monday effect regime ($\alpha_{con} = 0.66$) at 99 per cent significance. The threshold for the



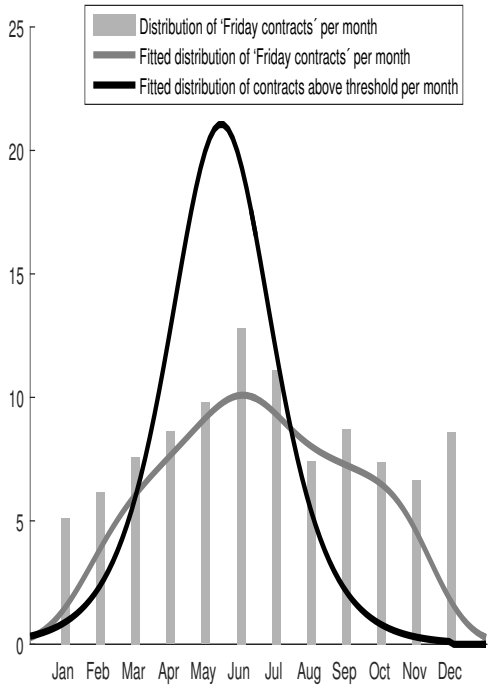
(a) Monday Effect: Raw vs Tar distributions, monthly



(b) Mon Effect: Raw and Fitted distributions



(c) Friday Effect: Raw vs Tar distributions, monthly



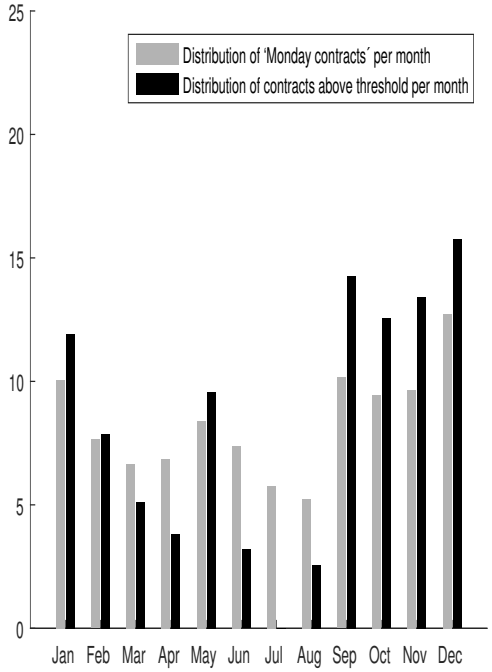
(d) Friday Effect: Raw and Fitted distributions

Figure 9: Shares for contracts over the calendar year: Restaurant Services (C51).

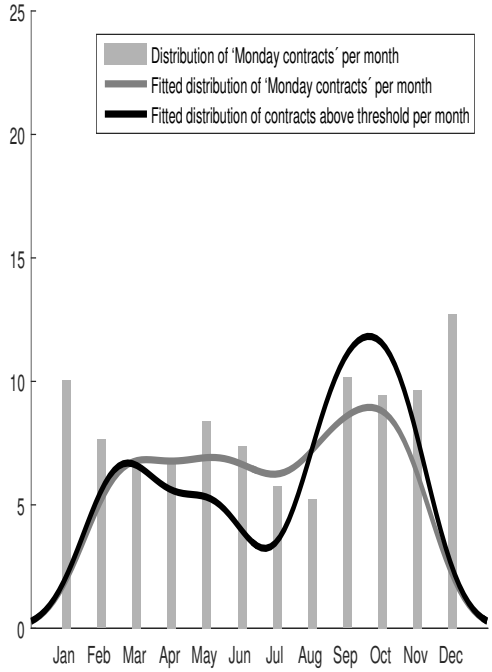
monday effect is 8.57 per cent, above the minimum share of contracts of this occupation over the sample which is 3.8 per cent, but far from the 42.5 per cent maximum share observed a day. The threshold model shows also the differences in the intensity of hirings along the calendar year for restaurant services. It is not only that the monday effect is more explained when this sector is over hiring (above the threshold), it is that the intensity of temporary contracts is significantly different during the summer period than over the rest of the year. Figure 9(a) compares the outcome of the threshold model with the raw data, and the difference does not seem large in this case though. Our *Tar* measure shows a smoother variation of the intensity of the monday effect all along the year compared with the raw data, more episodic. The outcome of the friday effect seems rather more informative. The threshold in this case is 21.1 per cent, and clearly there is a friday effect in hiring for this sector that is a lot more intense along the summer period indeed starting by May. The key is measuring relative to the aggregate friday effect. Remember finally that the share of contracts in restaurant services was negatively related with the aggregate friday effect, which is expected to occur out of the summer period for artistic, cultural, sports and other leisure related occupations.

The summer pattern needs not to be always the case [cf. Figures 10(a) to 10(d)]. The agriculture employment sector involve farm and forestry workers together with the fishing occupations. In this case, the distribution of contracts above the threshold is concentrated in the Fall and Winter terms, well above the raw data capture. The threshold is at 16.8 per cent of contracts (min 2.6, max 34.1 per cent), and the variability of the monday effect is mostly explained by this occupation when contracts are below the threshold ($\alpha_{pro} = 0.72$ vs. $\alpha_{con} = 0.92$, significantly different at 99 per cent). Figure 10(c) in its turn shows that the contracts with respect to the threshold for the friday effect (12.1 per cent) are more evenly distributed over the calendar year (note again the negative correlation in the aggregate). Thus, the difference between the Raw and the Tar distributions is more important for the monday than for the friday effect.

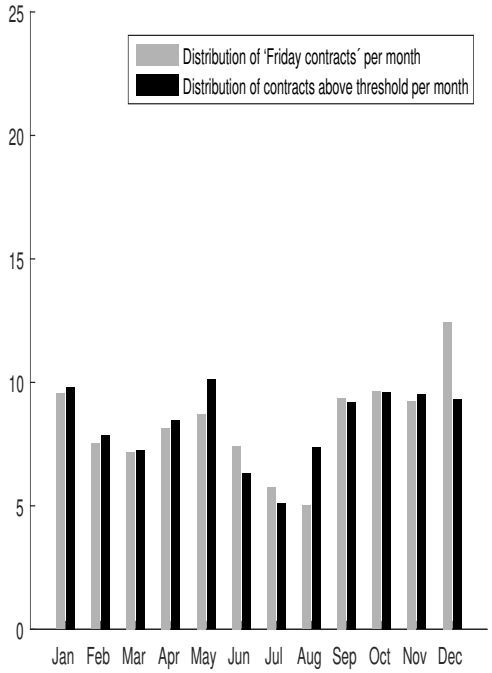
Figures 11(a) to 11(d) show how the two previous occupations complement. When combined they exhibit a very evenly distributed share of contracts above the threshold (19.6 per cent for the sum, for a max of 45.06 per cent). Thus, taking together these two categories eliminates the across calendar year variation [cf. Figure A.2, and notice again the importance in the share of these sectors in Table A.4]. This "combined occupations result" suggests a joint track of employment spells in these two occupations. Finally, the counter threshold (α_{con} above α_{pro}) effect is on sectors like sales persons, both in stores (52) and not in stores (54), or for the support workers in stores (98).



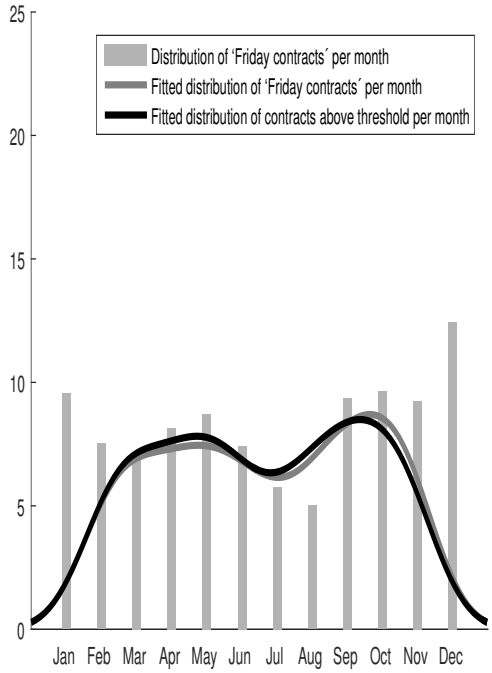
(a) Monday Effect: Raw vs Tar distributions, monthly



(b) Mon Effect: Raw and Fitted distributions

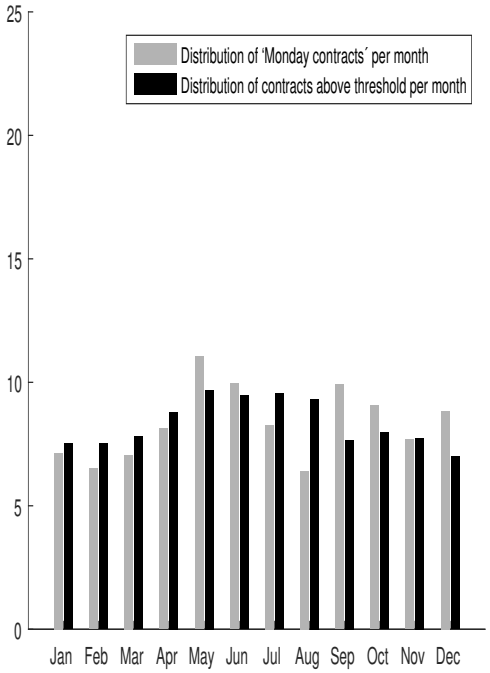


(c) Friday Effect: Raw vs Tar distributions, monthly

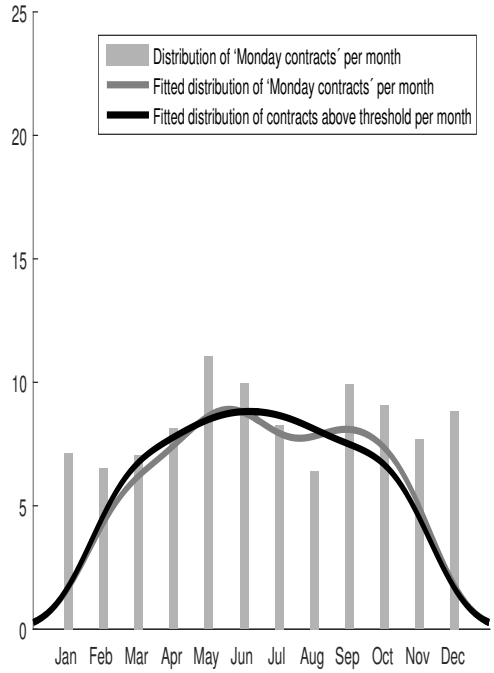


(d) Friday Effect: Raw and Fitted distributions

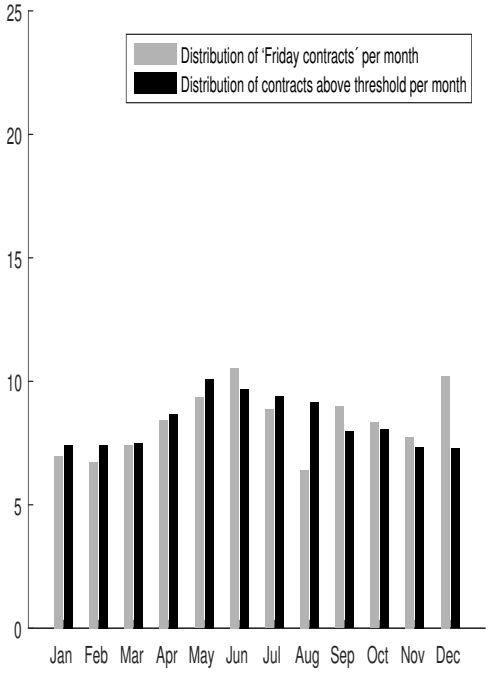
Figure 10: Shares for contracts over the calendar year: Elementary Agriculture (C95).



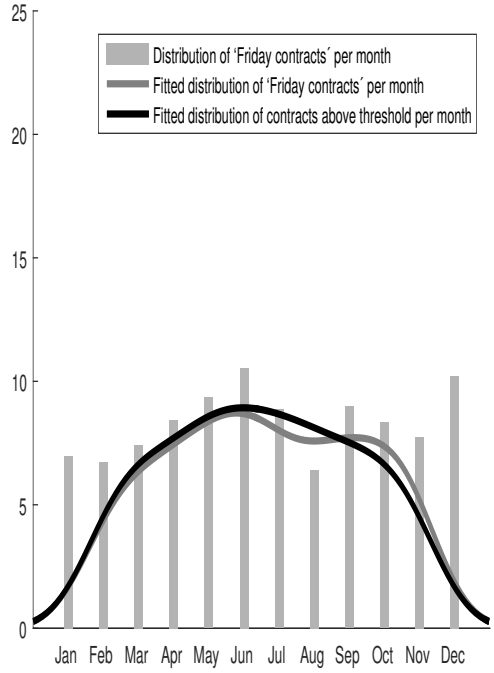
(a) Monday Effect: Raw vs Tar distributions, monthly



(b) Mon Effect: Raw and Fitted distributions



(c) Friday Effect: Raw vs Tar distributions, monthly



(d) Friday Effect: Raw and Fitted distributions

Figure 11: Shares for contracts over the calendar year: Restaurant Services (C51)+Elementary Agriculture (C95).

This points to sectors without a seasonal pattern of contracts or that are complements to other with a strong seasonal pattern in contracts, and it suggests channels of transmission for policies designed to mitigate calendar effects in temporary employment.

Summarizing, our findings in this part can be taken as an illustration of non-linearities in the strength of calendar effects and in their time variation, with consequences for the sectoral determinants of temporary contracts in Spain. We have comprehensively computed thresholds for all occupations and the corresponding variation of contracts over time. Particular analyses can be discussed upon request. We consider those analyses a promising tool for policy design (labour inspection) and policy evaluation (targeted time variation).

6 Concluding remarks

The goal in this paper has been to analyze when and how the huge episodes of aggregate employment creation and destruction we observe in the Spanish labour market occur. We document that those episodes follow fixed-term contracts associated to the calendar on a daily basis. Calendar effects are shown to vary over the business cycle and along the calendar year, driven by a number of occupations that are very representative of the productive model in Spain during the last decades.

The daily data illustrate the extent to which firms use fixed-term contracts of a very short duration and actually, under intense Monday and Friday effects. We measure that the Monday effect on employment creation nearly doubles the average day, whereas the Friday effect on employment destruction is roughly 20 per cent above. These effects intensify every year during the summer and along the business cycle boom. Measurement of the impact that each sector has on the Monday and Friday effects of job creation identifies five suspects: the construction sector (both elementary and skilled occupations), restaurant services, unskilled workers in manufacturing, and the educational occupations that add to the list in a tricky way. On the other hand, we find that occupations with stronger calendar effects exhibit higher temporary rates. We further identify within these occupations what is the period of the year their episodic behaviour is more prevalent. Our results can help to the design of sector and calendar oriented fraud prosecution policies.

To the best of our knowledge we are the first to use daily aggregate data from the labour demand side to analyze the precariousness of the dual labour market in Spain. Our results are

consistent with some well known findings from the labour supply side, as the high labour turnover, the disproportionate use of fixed-term contracts, or the recent increase of contracts of very short-duration even if signed as permanent. Our approach, however, associates these findings to the business cycle, and the sectoral composition of the economy, mostly through turnover in elementary occupations. For instance, we measure the prevalence of fixed-term contracts by the tourism sector during the touristic season, or the outlier pattern in the educational sector both beginning september and by the end of june. For other sectors like agriculture, while it is intensively using temporary contracts, the Monday effect is not important, and actually hiring exhibits a counter Monday effect at least once we control for the agricultural season. Consequently, our methods allow to measure highly temporary occupations, identify their calendar patterns, and provide a guide to evaluate the effectiveness of labour market policies for different sectors.

We observe in recent years an increase in both employment creation an destruction, as described here or discussed in Felgueroso et al. (2017). It is important to understand the reasons behind this. Is it that firms during the crisis have learned to squeeze the employment legislation to minimize costs? Or, is it the new digital technology that facilitates the "work on demand" processes? Computer and communication technologies allow firms to improve their daily management of hiring and firing. These mechanisms tend to translate all employment risk to workers, which is not only unfair, but also inefficient as far as corporations and the associated financial sector should be in better conditions to insure against employment risk. Further research should be devoted to investigate whether the calendar effects we have identified are backed by the same or different workers.

We have analysed calendar effects for a quintessential dual labor market: Spain. It would be interesting to examine the prevalence of these effects in labour markets released from excessive temporary hiring. The type of zero-hour contracts existing in the UK or the Netherlands, or the use of transitions to and from self-employment, might be playing a similar role to fixed-term contracts in Spain. It can be expected however, that those employment status, although equally precarious for workers, do produce spikes much smoother than the calendar effects identified in this paper.

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Appendix

A Aggregate Employment Data

Social Security Registers. The daily time series data contains information of the starting date and the termination date of all employment spells occurred in Spain during 2012-2017. The data considers both employed workers and self-employed. For this reason we refer to these employment data flows as *creation* and *destruction*. The daily time series are constructed using social security registers. We are going to use three different daily time series. The first is the daily number of affiliates to Social Security. The second (third) is the number of new registrations (number of de-registrations) daily to Social Security. Again, we interpret the number of new registrations as job creation and the number of de-registration as job destruction. The data have been obtained from the monthly publications of the Ministry of Labour and Social Security "Afiliación a la Seguridad Social". It is important to take into account that the register process only occurs on weekdays. In other words, the register data will only coincide with real data if the starting or the terminated date occurs on a weekday. If the starting date or the termination date is either weekend or bank holiday, the register will be recorded on the first subsequent weekday.

Table A.1: Job creation and destruction, averages annually

	Start Date (Employment Creation)					
	2012 (from march)	2013	2014	2015	2016	2017
Year	16171565	19856240	22029130	24218649	26026851	18070484
Month	1608134	1654687	1835761	2018221	2168904	2306501
Day	77748	79109	87765	96489	103281	106926
Affiliations	16442681	16357640	16775214	17308400	17849055	
	End Date (Employment Destruction)					
	2012 (from march)	2013	2014	2015	2016	2017
Year	16467783	19821826	21678496	23652636	25453723	18070484
Month	1629321	1651819	1806541	1971053	2121144	2247442
Day	79172	78971	86369	94234	101007	105872
Affiliations	16442681	16357640	16775214	17308400	17849055	

Table A.2: Job creation and destruction, weekly

	Employment Creation					
	2012	2013	2014	2015	2016	2017
Monday	152,326	149,546	163,579	180,316	194,709	213,230
Tuesday	59,102	64,878	74,893	80,931	86,707	88,360
Wednesday	61,080	58,906	63,829	75,435	76,657	81,803
Thursday	55,177	59,752	63,085	70,611	77,402	74,532
Friday	60,073	59,246	73,463	73,336	79,576	75,601

	Employment Destruction					
	2012	2013	2014	2015	2016	2017
Monday	127,214	127,138	139,246	157,840	179,398	186,648
Tuesday	69,268	70,075	79,504	86,903	85,179	89,059
Wednesday	63,294	64,718	63,797	72,307	74,418	77,214
Thursday	62,612	61,433	66,766	64,530	71,889	76,028
Friday	72,843	69,375	82,413	88,484	92,748	100,966

	Net Employment Creation					
	2012	2013	2014	2015	2016	2017
Monday	25,112	22,408	24,333	22,476	15,311	26,583
Tuesday	-10,166	-5,197	-4,611	-5,973	1,529	-700
Wednesday	-2,214	-5,812	32	3,128	2,239	4,589
Thursday	-7,434	-1,681	-3,681	6,081	5,513	-1,496
Friday	-12,769	-10,130	-8,950	-15,148	-13,171	-25,365

B A Comprehensive Calendar Effects Regression

Consider the daily variable "flow" can be assigned to aggregate employment creation, employment destruction, or the register of contracts. Then,

$$\log(\text{flow}_t) = \beta_M\, x_t^M + \beta_F\, x_t^F + \beta_R\,(1 - x_t^M - x_t^F) + \sum_{j=1}^{12} \gamma_j\, x_{j,t}^{BM} + \sum_{j=1}^{12} \eta_j\, x_{j,t}^{EM} + \sum_{j=1}^{S} \varphi_j\, x_{j,t}^{Seas} + \sum_{j=1}^{12} \gamma'_j\, x_{j,t}^{BM}\, x_t^M + \sum_{j=1}^{12} \gamma''_j\, x_{j,t}^{BM}\, x_t^F + \sum_{j=1}^{12} \eta'_j\, x_{j,t}^{EM}\, x_t^M + \sum_{j=1}^{12} \eta''_j\, x_{j,t}^{EM}\, x_t^F + \tilde{m}_t,$$

where dummy variables are labelled M(onday), F(riday), B(eginning)M(onth), E(nd)M(onth), and $Seas$(onal). Deterministic effects are interacted and $\tilde{m}_t$ accounts for autoregressive parts. Estimated effects can be decomposed in alternative forms consistent with the one reported in the main text.

Table A.3: Calendar effect for either the beginning or end of a month

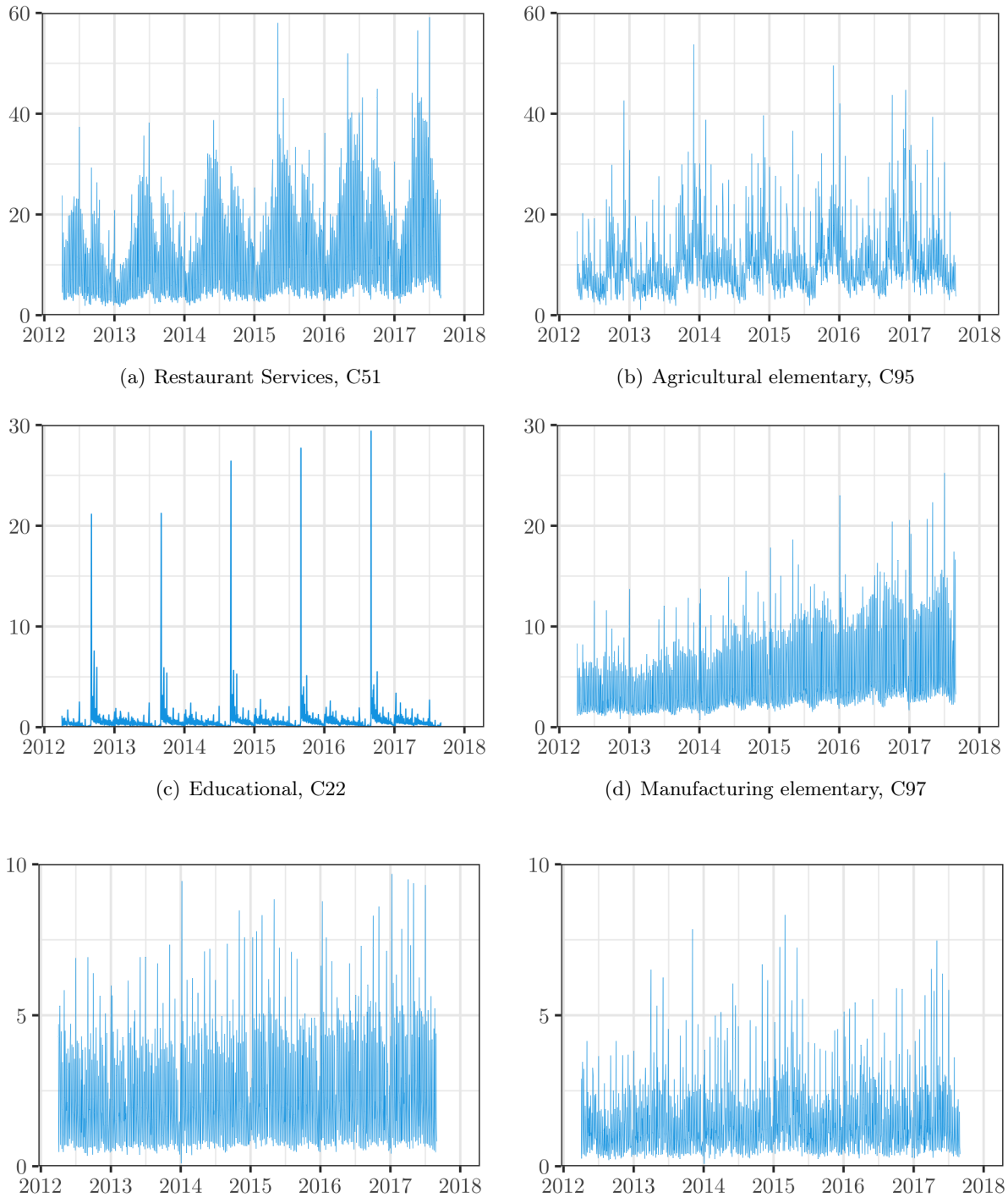
Monday (first day of the month)	Creation	Destruction
1st oct, 2012	312,747	296,082
1st apr, 2013	211,490	191,028
1st jul, 2013	387,714	333,288
1st sep, 2014	350,770	345,255
1st dec, 2014	254,673	211,969
1st jun, 2015	308,349	292,334
1st feb, 2016	264,599	259,412
1st aug, 2016	306,325	362,682
Friday (last day of the month)	Creation	Destruction
31 aug, 2012	36,463	231,433
30 nov, 2012	41,089	145,718
31 may, 2013	46,128	155,691
31 jan, 2014	37,067	130,630
28 feb, 2014	41,673	118,445
31 oct, 2014	53,982	179,482
31 jul, 2015	49,709	245,511
30 sep, 2016	70,357	288,176
31 mar, 2017	63,025	214,028
30 jun, 2017	84,320	341,334

C Contracts Data

Registers of Contracts. The daily data on the composition of new contracts correspond to the universe of registers at SISPE (Sistema de Información de los Servicios Públicos de Empleo/Official Register of Employment) of SEPE (Servicio Público de Empleo Estatal/Official Employment Information Administration) from the Spanish Ministry of Employment and Social Security. The sample of contracts goes from January 2011 to August 2017. This implies the use of about 100 million new contracts registered over the period. We restrict to "contract creation" because we only have information on the starting dates of contracts. All contracts are registered at SISPE with an identifier of the different occupations. The classification of occupations follows roughly the International Standard Classification of Occupations (ISCO-88). To make comparable the data on registered contracts with the aggregate Social Security data of employment spells we are using, we have assigned the contracts registered during the weekends or bank holidays to the closer subsequent labour weekday.

Table A.4: New contracts at SEPE, by sector

		2012	2013	2014	2015	2016	2017
C21	Health	1.70 %	1.81 %	1.78 %	1.80 %	1.78 %	1.73 %
C22	Educational	1.02 %	0.95 %	0.90 %	0.87 %	0.86 %	0.57 %
C29	Artistic, Literary & Cultural	1.79 %	1.83 %	1.84 %	1.87 %	1.93 %	1.93 %
C37	Cultural & Sport services	2.90 %	2.88 %	2.88 %	3.02 %	3.15 %	3.01 %
C44	Leisure services	2.05 %	1.97 %	1.90 %	1.95 %	1.94 %	1.95 %
C51	Restaurant services	12.78 %	12.95 %	13.32 %	13.67 %	14.26 %	14.43 %
C52	Shop assistants	5.32 %	4.91 %	4.88 %	4.85 %	4.80 %	4.70 %
C54	Sellers out of shops	1.87 %	1.71 %	1.68 %	1.61 %	1.62 %	1.49 %
C56	Caring	2.31 %	2.25 %	2.25 %	2.26 %	2.29 %	2.20 %
C58	Personal services	2.41 %	2.21 %	2.18 %	2.16 %	2.24 %	2.17 %
C71	Construction skilled	3.43 %	3.32 %	3.18 %	3.14 %	2.91 %	3.04 %
C84	Urban & Road transport drivers	2.51 %	2.55 %	2.57 %	2.60 %	2.63 %	2.69 %
C91	Domestic cleaning	0.90 %	1.42 %	1.25 %	1.15 %	1.06 %	0.98 %
C92	Market cleaning	7.70 %	7.16 %	6.88 %	6.86 %	6.84 %	6.71 %
C93	Food preparation	1.62 %	1.72 %	1.87 %	2.00 %	2.17 %	2.26 %
C94	Services elementary	2.44 %	2.37 %	2.26 %	2.24 %	2.12 %	2.13 %
C95	Agricultural elementary	13.96 %	15.07 %	15.11 %	13.79 %	13.32 %	13.25 %
C96	Construction elementary	2.02 %	2.21 %	2.03 %	2.01 %	1.77 %	1.81 %
C97	Manufacturing elementary	5.15 %	5.33 %	6.00 %	6.54 %	6.95 %	7.41 %
C98	Shelf filers & storage	2.70 %	2.58 %	2.60 %	2.76 %	2.87 %	2.83 %



(a) Restaurant Services, C51

(b) Agricultural elementary, C95

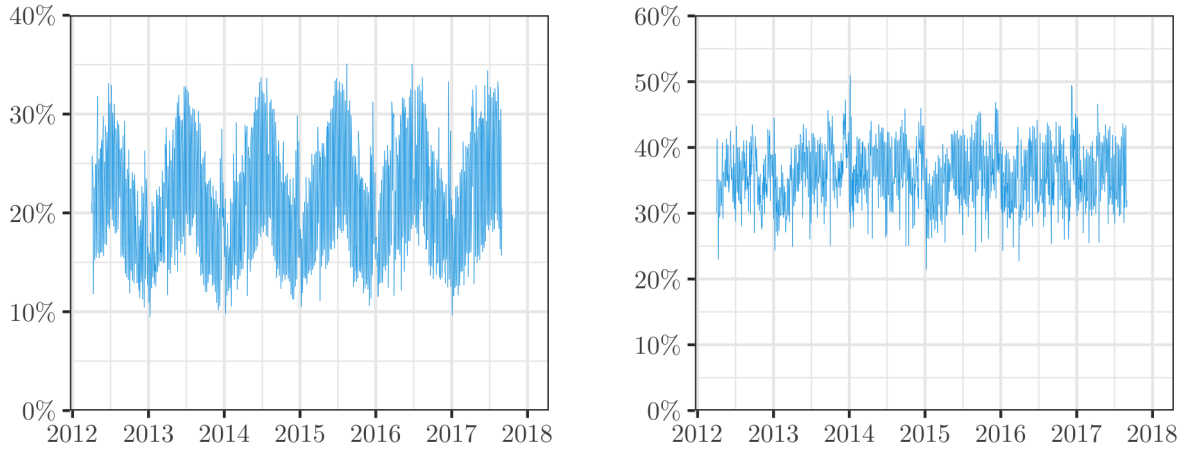
(c) Educational, C22

(d) Manufacturing elementary, C97

(e) Construction skilled, C71

(f) Construction elementary, C96

Figure A.1: Daily contracts in selected sectors according to SEPE (note scale from top to bottom in thousands: 60000, 30000, 10000).



(a) Accommodation (C51+C92)

(b) Accommodation & Agriculture (C51+C92+C95)

Figure A.2: Evolution of the share of contracts over total in Accomodation (C92) plus Restaurant Services (C51), and together with Elementary Agriculture (C95) occupations, 2012-17.