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Post-Great Recession Labor Market Dynamics in Spain: A Comparison of Alternative Datasets

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Abstract

Using Social Security (SocS) records covering the universe of Spanish employees and firms, we compare firms' employment dynamics between 2013–2024 to those obtained from the Bank of Spain's microdata drawn from firms' balance sheets (CBI) as well as those of U.S. firms. Compared with CBI, SocS reveals less volatile aggregate employment growth and higher job reallocation rates driven by firms' large employment adjustments. Worker reallocation in Spain remains below U.S. levels and did not decline after the 2022 labor reform. SocS also highlights the central role of small firms in Spanish job creation and documents a left-shifted firm-size distribution relative to the U.S. Start-ups entering smaller, having lower survival probabilities, and weaker employment growth among survivors all contribute to a smaller Spanish firm size.

JEL classification

J21, J40, J60

Keywords

job flows, worker flows, firm dynamics

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1 Introduction

Since the through of the global financial crisis in 2014, total jobs in Spain have grown by almost 33 percent (%), making it nowadays one of the EU member states where employment is growing the fastest. At the same time, the Spanish labor market has traditionally suffered from high dualism, with a high share of workers enjoying low job security (see, e.g., Bentolila, Cahuc, Dolado, and Barbanchon, 2012; Costain, Jimeno, and Thomas, 2010), low productivity growth (see, e.g., Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez, 2017; García-Santana, Moral-Benito, Pijoan-Mas, and Ramos, 2020), small average firm size (see, e.g., Pagano and Schivardi, 2003), and low employment growth rates of start-ups (see, e.g., Villegas-Sanchez, 2025; Riveiro, 2025).

When analyzing these phenomena from the perspective of firms, existing studies on Spain have relied on non-representative yearly firm survey data stemming from the Spanish commercial register provided either by the Banco de España (BdE in short) through the *Central de Balances Integrada* (CBI, hereafter) or the Bureau van Dijk's ORBIS-AMADEUS data. Almunia, Lopez Rodriguez, and Moral-Benito (2018) show that, despite excluding the financial sector, these datasets are indeed successful in matching several aggregate employment dynamics. Moreover, Fernández Cerezo et al. (2024) document that the CBI also does a good job in capturing the distribution of firm size across Spanish regions, even though they point out to some under-representation of small firms. At the same time, so far there has been no current micro-level data that allows to assess the representativeness of these data sources as regards firm dynamics.

This paper fills that gap by building a new yearly firm-level data set covering the universe of Spanish dependent employment based on social security (SocS, henceforth) records from 2013 to 2025.[1] Access to this data allows us, for the first time, to compute moments of business dynamics for the universe of Spanish firms. This information is being used for two purposes. First, given their prominence in analyzing firm dynamics among researchers, we compare the above-mentioned CBI survey data to the universe of Spanish firms in terms of business dynamics moments. Second, we compare Spanish firm dynamics to the U.S. paying special attention to the relatively small firm size and low employment growth rates of start-ups in Spain.

Similar to Almunia et al. (2018), we begin by studying aggregate employment dynamics and highlight two new issues with the CBI data. First, the CBI not only oversamples large firms, but this selectivity becomes worse between 2013 and 2024, which manifests itself in a too high growth of average firm size. Second, we find that aggregate employment growth is too volatile in the CBI. This finding is unrelated to the oversampling of large firms or from the exclusion of the financial sector. Instead, we find that the number

[1] We make the underlying aggregate data series available on this site.

of firms is excessively volatile in the CBI, mainly because some firms appear to have stopped providing data during the COVID-19 recession.

Second, we follow the seminal work of Davis and Haltiwanger (1992) and describe business dynamics in terms of job reallocation. With SocS data, we find that the Spanish economy is quite similar to the U.S. in this respect: about 22% of jobs are reallocated between firms every year. In fact, in terms of firm entry and exit, Spain displays even somewhat higher rates than the U.S. Reliance instead on the CBI data understates the amount of Spanish job reallocation by about 50%. We show that the CBI misses particularly large employment adjustments by firms, including firm entry and firm exit. We also show that the CBI plays down business dynamics, in part, because it understates the share of workers with temporary employment contracts (TC) relative to the number with permanent employment contracts (PC) before 2022. This becomes a serious shortcoming since job reallocation is more than twice as high among the former than in the latter type of labor contracts.

The share of TC fell from around 27% to 12%, following the labor market reform in 2022 which replaced 40% of those contracts with intermittent PC. We find that the reform had no visible effect on the amount of job reallocation, a result which fits well with theories in the spirit of Pries and Rogerson (2005) that argue that job reallocation is independent of labor market institutions. Our new SocS data also allows us to evaluate its effect on worker reallocation and worker churn. We show that it also had no visible effect on those. Put differently, to the degree that the reform aimed at increasing job stability for workers, it has so far not succeeded.

Third, we turn a better understanding of the small average firm size in Spain. Mapping out employment shares across firm sizes shows that Spain has 20 percentage points (pp.) less employment at firms with at least 500 employees and 7 pp. more at firms with fewer than 5 employees compared to the U.S. Consistent with the earlier studies, we show that the CBI understates those differences. Disparities are even larger in manufacturing, where, unlike the U.S., the employment share at firms with at least 500 employees is lower than in the overall Spanish economy.

Finally, we investigate whether (missing) employment growth of start-ups helps rationalize the missing large firms in Spain. We show that start-ups enter on average with 2 fewer employees in Spain than in the U.S. and grow on average by 3.3 employees less than U.S. start-ups over the first twelve years of their existence. What is more, survival rates are lower in Spain, e.g., after 6 years, 52% of U.S. start-ups are still operating against only 42% of their Spanish counterparts. In other words, part of why Spain is missing large firms is that its start-ups do not grow sufficiently and die at a too high rate, being replaced by relatively small new entrants. We also show that once we condition on age, the CBI data provides substantially similar results to the ones from the universe of firms.

As with the firm size disparities, differences in start-up employment growth are even more pronounced in the manufacturing sector. Over the first 12 years, the average U.S. start-up grows by 5.4 workers more than a Spanish start-up. Strikingly, the low growth is partially explained by firms not reaching the size category of at least 500 employees. Their employment share by cohort slightly falls for the first 12 years in Spain while it increases by more than 10% of a cohort's employment in the U.S.

The rest of the paper is structured as follows. Section 2 describes the three datasets used in the different comparisons. Section 3 deals with aggregate employment dynamics and the effects of the Spanish 2022 labor-market reform on worker flows. Section 4 examines the firm size distribution, including life-cycle moments for firm size and survival probabilities. Finally, Section 5 concludes. An appendix gathers some extra Figures mentioned in the main text.

2 Data sources

This section is devoted to describe the three data sources (two for Spain and another one for the U.S.) that are used throughout the paper.

2.1 Spanish Social Security (SocS)

Our novel firm-level dataset is based on the universe of Spanish social security (SocS) records. The administrative procedure requires employers and self-employed in all sectors to report the starting and ending dates of any employment relationship between firms and workers. The files we access include information on employment status and characteristics for more than 20 million affiliates every month. Workers are either self-employed or linked to a firm that has a unique identification number (CCCP, Código de Cuenta de Cotización Principal). Our analysis focuses on employees and, therefore, we drop all self-employed, who represent about 23 percent of the observed affiliations.[2] As in the other two datasets, the unit of production is the firm rather than establishments. Moreover, to align this data with one from the U.S. (see below), we drop firms with industry codes associated with public administration (CNAE sector P) or private households (CNAE sector Q).[3] Lastly, to facilitate the comparison to the CBI, we also compute some statistics excluding the financial sector (CNAE sector L) from the SocS data.

[2]We identify self-employed through their specific contribution regime (Régimen de Cotización).

[3]The data coverage of civil servants and military personnel is incomplete, and occasionally there might be missing data on the type of contract or sector.

To aggregate the data to the firm level at annual frequencies, an end-of-period definition is used. In particular, a worker is defined as employed in a given firm at the end of the year when he/she works there at the end of January.[4] This gives us an annual dataset covering 2013–2025 with an average of 13,823,785 workers and 1,932,708 firms per year observations. For each firm, we know its location, the number of employees, E_{it}, either with PC or TC, as well as its sector of activity.

Given the definition of employment, job flows are computed as $JF_{it} = E_{it} - E_{it-1}$. In addition, when a plant reduces employment within a year ($JF_{it} < 0$), we count this as job destruction, JD_{it}, while, when it increases employment, ($JF_{it} > 0$), this is counted as job creation, JC_{it}.

As timing convention, we shift the time period one period back. For example, employment on January 31st 2015 is displayed as employment in 2014, and the job creation taking place between March 21st, 2014 and 2015 as job creation in 2014.

Since the data lacks a definition of firm entry or exit, we consider a firm as having newly entered the market in a given year when it has the first time positive employment, $E_{it} > 0$. If the firm subsequently decreases its employment to zero in a given year and reappears in a later year, we do not consider this a new entry event. Note that, by definition, we consider firm entry as the first year a firm has dependent employees and not necessarily when it was founded. Similarly, we consider a firm to exit in year t if this the last time it appears in the dataset and does not have end-of-period employment, $E_{it} = 0$. Note that the entry definition becomes somewhat more stringent as we move forward in time due to the left-censoring of our sample. For example, we consider a firm entering in 2013, even when it truly entered in the year 2010 (before our sample starts), if it stops having dependent employment for several years, and then hires again a worker in 2013. By contrast, a similar firm that truly starts operating in 2013, stops having dependent employment until 2016 and then hires a worker again in that year would be considered entering in 2013 and not in 2016. Likewise, the exit definition becomes somewhat more stringent as we move back in time because of the right-censoring of our sample.

2.2 Central de Balances Integrada (CBI)

The CBI is an administrative firm-level data set maintained by the BdE which significantly expanded the coverage of the former *Central de Balances* (CBBE). It covers the non-financial sector and, additionally, excludes companies operating in public administration and defense, social security, education, health and social services, as well as in agriculture, livestock, forestry and fishing, and household activities. It relies on the bal-

[4] Since our data starts in January of 2013, we define flows between January of each year to avoid losing that year.

ance sheet data that all limited liability companies, partnerships by shares, and mutual guarantee companies have to report annually to the commercial register. Additionally, non-covered firms can participate voluntarily. The underlying data source is the same as that used by the ORBIS-AMADEUS data, and we discuss these two datasets interchangeably. The data starts in 1995; however, as our SocS data is only available from 2013, the sample is restricted to 2013–2024 in the sequel. At the time of writing this paper, only part of the 2024 data was available which, as discussed below, implies that this year cannot be used for some of our analysis.

Some firms do not report their information on time and are excluded. To address this attrition problem, it is possible to merge the CBI data with the SABI database (Iberian Balance-Sheet Analysis System), sometimes labeled the *extended* CBI. Although this is this data that Almunia et al. (2018) compare to national accounts, our comparison is restricted to the CBI since this is the only data that the BdE makes freely available to external researchers.

The employment definition in the CBI corresponds to the median number of employees over a year. Note that all they ask firms is for their total number of employees but not for how many workers did they newly hire/separate in a given year. This prevents the use of CBI to measure worker reallocation rates (see section 3.5 below).[5] The Statistical Department of the BdE cleans the raw data to ensure that basic accounting criteria, as well as meeting basic consistency between the number of employees and wage payments.[6] In addition, we drop observations with non-positive employment during the current and previous year, which yields our measure of the number of active firms in a given year.

This dataset asks for the year in which the firm was founded. Thus, our first measure of firm entry relies on the founding year, besides further conditioning on the non-existence of the firm in previous years. On top of that, use is also made of a second entry definition analogous to the one used in the SocS data. Accordingly, a firm is defined as having entered the market when it has the first time positive (median) employment in t, regardless of its founding year. Finally, we define firm exit as the last year the firm is observed in the data. Defining entry and exit based on the first/last year of observation has the problem that the data does not cover the universe of firms since a firm may stop reporting either because it was no longer obliged to do so or simply due to not fulfilling its reporting obligations.

[5]For example, firm can have 10 workers last year and 10 workers this year, i.e., 0 job flows. Yet, it could have hired 2 new workers and separated from 2 old workers, i.e., 4 worker flows. In the CBI, this impossible to know since all it is reported is 10 workers last year and this year

[6]The final data is a collaborative effort by BELab, Banco de España and CORPME (Colegio de Registradores de la Propiedad y Mercantiles de España).

2.3 U.S. Business Dynamics Statistics (BDS)

Regarding the U.S. labor-market flows data, we resort to its Business Dynamics Statistics, which is a popular dataset for these purposes (see Haltiwanger, Jarmin, and Miranda, 2008, 2012). The BDS reports employment, job creation, and job destruction for U.S. firms at an annual frequency. As in the Spanish SocS data, its employment concept is end-of-period. In particular, the stock of employment refers to March 21st of each year; hence, job flows are computed as those taking place between March 21st of two consecutive years. As a timing convention, we will shift the time period one period back, e.g., display employment on March 21st 2015, as employment in 2014, and the job creation occurring between March 21st, 2014 and 2015 as job creation in 2014. The last data observation available is from March 2023, i.e., 2022, so that the sample covers 2012–2022.

As in the two Spanish datasets, the BDS excludes all self-employed, as well as most governmental employees, railroad workers, and private household employees. Similar to the SocS data, BDS uses the concept of imputed firm age, i.e., firm entry is defined as the first occurrence of the firm with positive employment. Moreover, firm exit is defined as the firm reducing its employment size to zero.

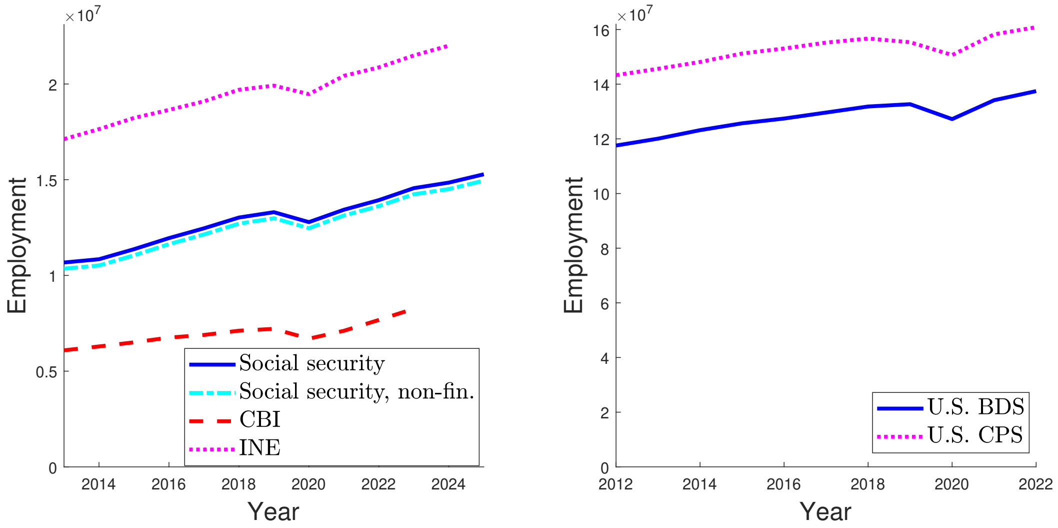
3 Aggregate employment dynamics

3.1 Employment

Figure 1(a) displays the total number of employees over time in the two Spanish datasets and in the one for the U.S., and compares these workers to the total number of workers in each of the two economies. The right panel shows that the BDS captures 83% of U.S. workers, a ratio that is relatively stable over time. The left panel, in turn, shows that this number is lower in Spain, reflecting its higher share of self-employed workers. The SocS data captures 62% of total employment in 2013 with that share reaching 67% in 2024. The same panel shows that the CBI data captures slightly about half of such employment. Note that the inclusion of the financial sector in the SocS data explains little of the additional coverage.

Figure A.1 in the appendix shows that the CBI captures about 39% of the total number of firms in Spain, and this ratio is also highly stable over time. The CBI capturing more employment than firms implies that the average firm is bigger in this dataset. Figure 2 highlights this phenomenon over time. It shows that the CBI's selectivity towards large firms has increased somewhat over time. In 2013, the average firm size was 3.23 employees higher in the CBI than in the SocS data. By 2023, this difference has grown to 4.64 employees.

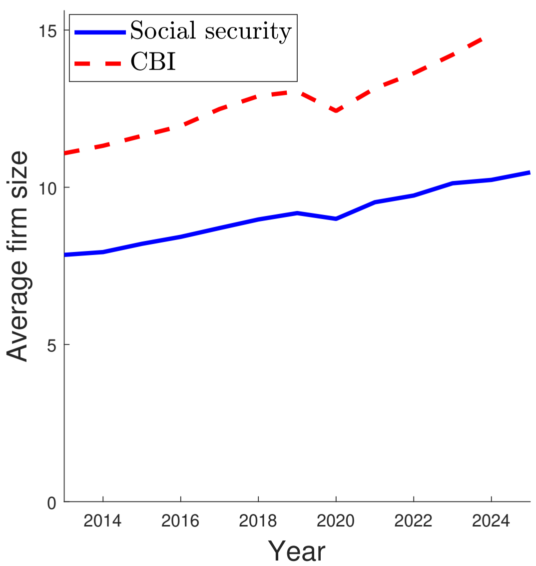
Figure 1: Employment



(a) Employment Spain (b) Employment U.S.

Note: This figure displays the total number of employment. Employment in SocS records refers to employees in the non-household, non-governmental administration sectors at the end of January of the following year. The CBI measures employees in the non-household, non-governmental administration, and non-financial sectors as the median employment during a year. Social security, non-fin. excludes the financial sector. The data from INE refers to the total number of people working at the end of the year. The BDS refers to employees in the non-household, non-governmental sectors as of March 15th of the following year. The CPS refers to the total number of people working at the end of the first quarter of the following year.

Figure 2: Average firm size



Note: This figure displays the total number of employees relative to the total number of active firms in a year. See the figure notes of Figure 6 for the employment definitions.

3.2 Cyclical employment growth

Next, to get a sense of business cycle fluctuations, we turn to employment growth rates. To define flow rates, we follow Davis and Haltiwanger (1992) in using the average of contemporaneous and lagged employment, namely, $D_{it} = [E_{it} + E_{it-1}]/2$ in the denominator which ensures that the resulting rates are bounded between -2 (exiting firms) and $+2$ (entering firms):[7] Hence, the aggregate employment growth rate is given by

$$EGR_t = \frac{\sum_i JF_{it}}{\sum_i D_{it}}. \tag{1}$$

Figure 3 displays the rates from the different datasets together with the corresponding changes in the unemployment rate.[8] While the 2014-2017 boom period was somewhat stronger in Spain than in the U.S., the COVID-19 downturn was more pronounced in the U.S., which is consistent with the widespread use of furlough schemes (ERTE) in Spain during the pandemic (see Diaz, Dolado, Jáñez, and Wellschmied, 2025). Finally, in both instances, employees exhibit a smoother growth rate than total employment.

Regarding the two Spanish datasets, employment growth rates move in a remarkably similar way (with a correlation of 0.92). However, the business cycle is somewhat more pronounced in the CBI data. Comparing 2017 with 2020 (the COVID-19 year), this growth rate falls by 10 pp. in the CBI data but only by 7.5 pp. in the SocS data. We find that the differences in sample composition cannot explain the CBI higher employment cyclicality. In other words, we find stronger cyclical fluctuations in the SocS data than in the CBI data, even conditioning on firm size. Similarly, while we find that the inclusion of the non-financial sector explains basically none of this difference, Figure A.1 in the appendix shows that the cyclicality in the number of firms provides an explanation of part of this difference. That is, the number of firms fell more strongly during the COVID-19 recession in the CBI than in the SocS data and recovered more strongly after 2021.

3.3 Job Reallocation

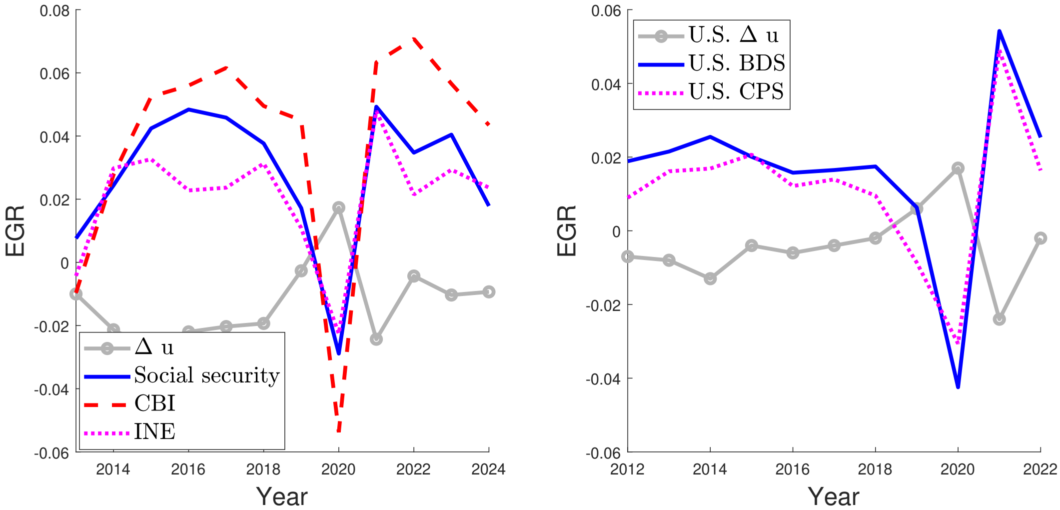
Davis and Haltiwanger (1992) were the first to point out that studying gross job flows leads to additional insights into the labor market beyond those obtained from studying net employment changes. Since then, a large body of academic literature has studied gross job flows, and they also feature prominently in the U.S. economic policy debate. In fact, the Bureau of Labor Statistics supplements its monthly report on net job changes in the U.S. economy (Current Employment Statistics) with a more detailed quarterly report focused on the amount of gross job flows (Business Employment Dynamics).

The Spanish statistical agency (INE), so far, reports only net job changes. Early attempts to measure the amount of gross job flows in Spain include Dolado and Gomez-Salvador (1995), using the old version of the CEBE for large manufacturing firms, and

[7] See Davis and Haltiwanger (1992) for a thorough discussion of these rates.

[8] To be consistent with the different timing conventions, the change in the unemployment rate in Spain is between the ends of last quarters, while, in the U.S., it is between the ends of first quarters.

Figure 3: Employment growth rate



(a) Employment Spain (b) Employment U.S.

Note: This figure displays the employment growth rate and the change in the unemployment rate. See the figure notes of Figure 6 for the employment definitions. Unemployment rates are obtained from the St. Louis Fed FRED.

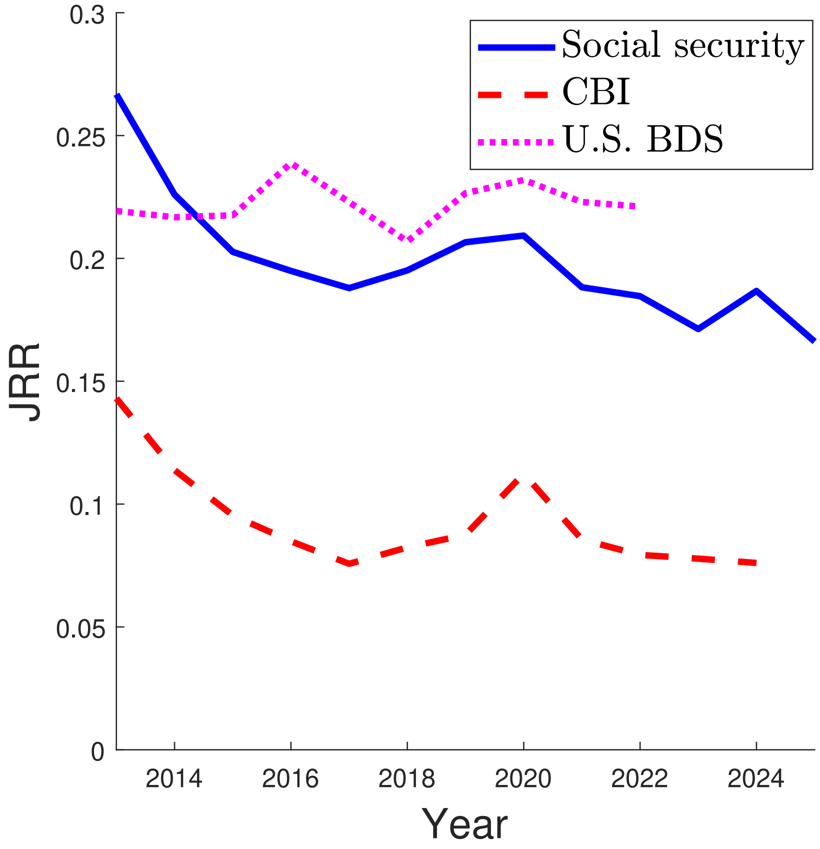
Díaz Moreno and Galdón-Sánchez (2000), using Social Security records for firms with at least 10 employees from 1995.[9] The first authors find an annual job turnover rate (the sum of the job creation and job destruction rates) of just 7.1%, while the second authors report a much higher rate of 31.1%.

Instead of reporting the job turnover rate, we follow BDS in reporting the so-called job reallocation rate, which measures the excess of job flows in an economy once net employment growth is accounted for: $JRR_t = JCR_t + JDR_t - EGR_t$, that is, the reallocation of jobs across different firms that is not arising from changes in the total number of jobs.

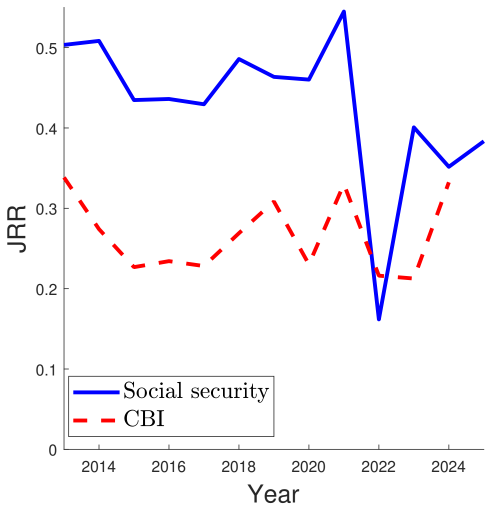
Figure 4(a) plots the job reallocation rates in the different datasets. According to the SocS data, this rate is remarkably similar to the one in the U.S: about 23% of all jobs are reallocated across firms. This finding is consistent with the argument in Pries and Rogerson (2005) that advanced economies should share a similar amount of job reallocation. By contrast, the CBI understates job turnover by more than one half. Moreover, though the decreasing time trend in the CBI is broadly consistent with the SocS data, the former overstates the spike in 2022. Regarding the fall in turnover rates after 2013, Carrillo-Tudela, Clymo, Fuente, Visschers, and Zentler-Munro (2025), using data from the Spanish Labor Force Survey, show that workers directing much of their

[9]Other studies on labor market flows in Spain are García-Serrano and Malo (2002), and Estrada, Izquierdo, and García Perea (2002). The former uses 1993-1996 data from Encuesta de Coyuntura Laboral (ECL-INE) to study the effects of collective bargaining on flows, while the latter use the Spanish LFS (EPA) for 1987-2000 to analyze the role of TC in explaining those flows.

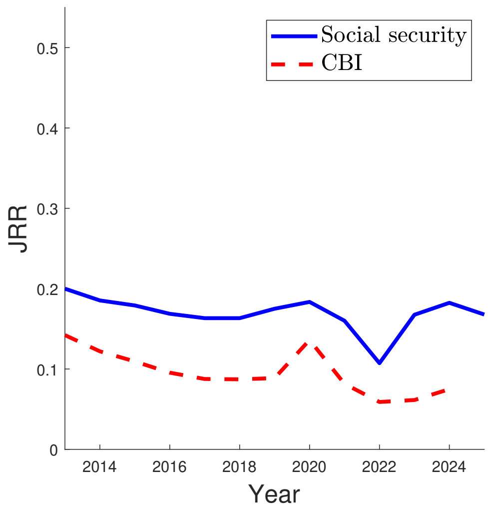
Figure 4: Job reallocation rate



(a) Total economy



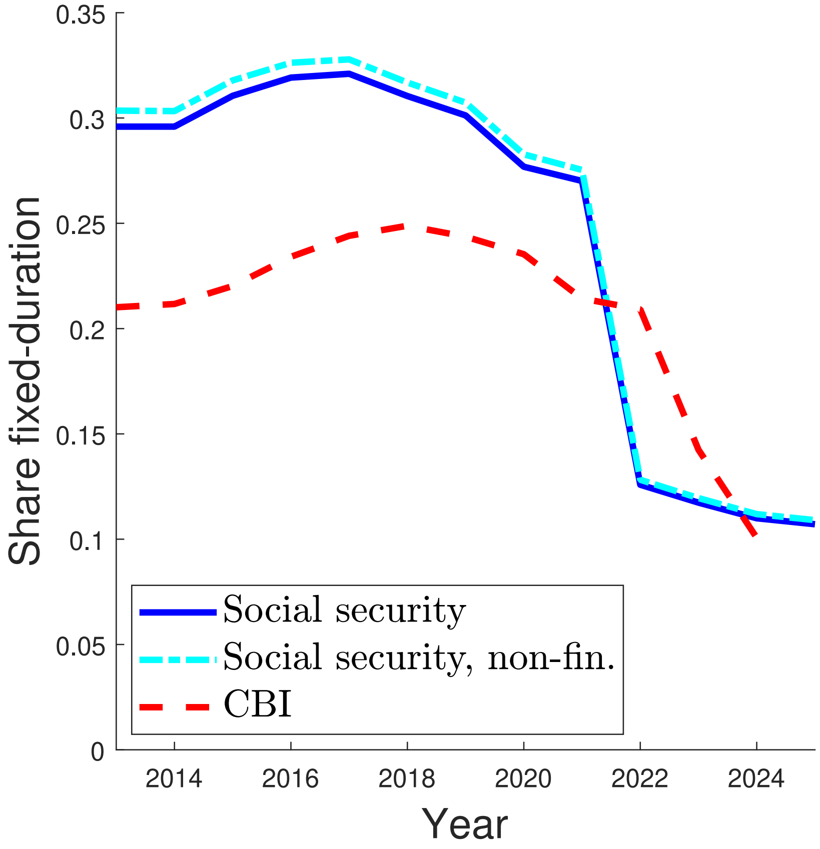
(b) Temporary



(c) Permanent

Note: This figure displays the job reallocation rate, defined as the sum of the job creation and destruction rates net of the employment growth rate. The top panel displays the total economy. The bottom left panel displays only fixed-term contracts. The bottom right panel displays permanent contracts. See the figure notes of Figure 6 for the employment definitions.

Figure 5: Share of fixed-duration contracts



Note: This figure displays the share of fixed-duration contracts in Spain. See the notes of Figure 6 for the employment definitions.

search intensity towards low matching efficiency and job finding rate industries (e,g., *Other Services*), is a contributing factor to the decreasing job reallocation.

To better understand why the job reallocation rate is low in the CBI, we next turn to the main specificity of the Spanish labor market, namely, its dual nature (see, e.g., Bentolila et al., 2012; Costain et al., 2010). In effect, while high-tenured workers can count on generous employment protection, more than one-fifth of workers in Spain have had TC, often lasting less than 3 months, until the labor market reform of 2022. Given the high flexibility of TC, one would expect job turnover to be much higher for these fixed-term contracts than for PC.

Figure 4(b) and Figure 4(c) show that this is indeed the case regardless of the dataset. Moreover, it shows that the CBI matches the level of conditional job turnover flows somewhat better than the overall level of job turnover. In effect, it captures 56% of the permanent job turnover rate and 66% of the temporary job turnover rate.

To grasp why the CBI matches better conditional job turnover than overall job turnover, Figure 5 displays the share of workers holding TC. Consistent with earlier stud-

Table 1: Employment growth rate distribution

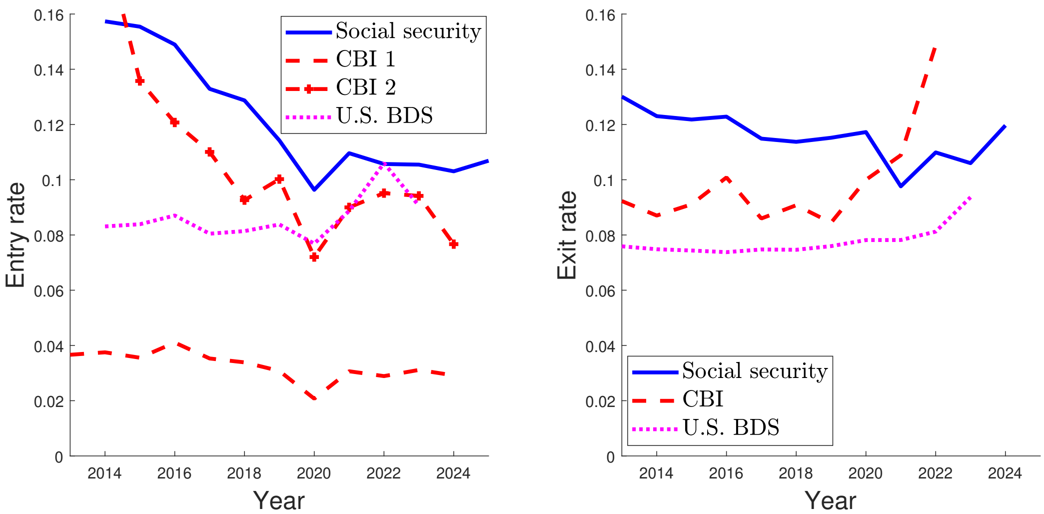
	Social security Employment	CBI Employment	Social security Firms	CBI Firms
$EGR_{it} = -2$	2.37	0.25	12.80	2.34
$-2 < EGR_{it} < -1$	0.61	0.40	0.56	1.92
$-1 \geq EGR_{it} < -0.6$	1.46	0.80	4.09	2.76
$-0.6 \geq EGR_{it} < -0.3$	2.81	2.35	3.19	4.61
$-0.3 \geq EGR_{it} < -0.15$	5.59	5.06	4.01	5.81
$-0.15 \geq EGR_{it} < -0.05$	9.80	11.66	2.37	7.27
$-0.05 \geq EGR_{it} < -0.01$	9.24	11.88	0.63	4.59
$-0.01 \geq EGR_{it} \leq 0.01$	18.69	14.48	40.17	29.05
$0.01 < EGR_{it} \leq 0.05$	13.04	16.08	0.76	5.48
$0.05 < EGR_{it} \leq 0.15$	17.45	20.72	3.13	9.81
$0.15 < EGR_{it} \leq 0.3$	9.20	9.66	5.16	8.04
$0.3 < EGR_{it} \leq 0.6$	4.72	4.38	4.09	6.25
$0.6 < EGR_{it} \leq 1$	1.98	1.09	4.83	3.32
$1 < EGR_{it} < 2$	0.71	0.50	0.65	2.62
$EGR_{it} = 2$	2.34	0.68	13.54	6.10

Note: This table compares the firms' employment growth rate distribution from Spanish SocS data and the CBI. The first two columns display employment-weighted distributions. The last two columns display the share of firms in each bin. To compute the employment growth rate, we use in the denominator the average of current and last period's employment.

ies that compare this share to the one obtained from the Spanish Labor Force Survey, (see Auciello, Pijoan-Mas, Roldan, and Tagliati, 2023; Pijoan-Mas and Roldan-Blanco, 2024), we find that the CBI understates this phenomenon prior to 2022. Specifically, it yields a TC share of about 22% before 2022 against higher 30% in the SocS records. Accordingly, the CBI understates the overall job turnover rate partly because it downplays the number of TC. At any rate, both datasets show a large decline of TC following the labor reform of 2022 with their share dropping to around 13% in the SocS data and to 10% in the CBI.

Finally, we examine whether the higher job reallocation in the SocS data than in the CBI may be the result of more firms adjusting their employment in that dataset and/or the possibility that those firms adjusting employment carry out larger adjustments. To tell the two possibilities apart, Table 1 displays bins of the employment growth rate distribution for the two datasets. The last two columns display the number of firms in each bin, and the first two columns display the D_{it}-weighted distribution. As can be observed, both approaches tell a similar story. The number of firms and the total employment share at non-adjusting firms, $-0.01 \geq EGR_{it} \leq 0.01$, is higher in the SocS data than in the CBI. Consequently, the higher job reallocation in the SocS data arises from more firms/employment belonging to the tails of the employment growth rate distribution.

Figure 6: Entry and exit rates



(a) Entry (b) Exit

Note: This figure displays firm entry and exit rates, according to the following definitions. Entry in S:S: First year a firm has positive end-of-period employment. CBI 1: Present year equals the reported founding year, and no previous occurrence. CBI 2: First year a firm reports positive median employment. BDS: First year a firm has positive end-of-period employment. Exit in SocS and CBI: Last year a firm reports positive employment. Exit in BDS: No employment in t and positive employment in $t-1$.

3.4 Firm entry and exit dynamics

Since firm entry and exit are relevant sources of job reallocation, their time-series behavior has been extensively analyzed. For example, Haltiwanger (2012) shows a secular decline of those rates in the U.S., which could point to reduced business dynamism. Similarly, Hopenhayn, Neira, and Singhania (2022) show that such a trend could be behind the increasing employment concentration at large firms. Lastly, Lee and Mukoyama (2015) study the cyclicality of those rates, concluding that the entry rate is far more cyclical than the exit rate.

Figure 6(a) compares entry rates, defined as the number of new firms relative to the total number of active firms in a given year, for both economies. In the SocS data, 12.2% of all firms enter within a year, which is about 30% higher than in the U.S. Using the definition of a firm first appearing in the CBI, we find a similar rate to the SS. However, using the definition of reported firm age, a much lower rate of just 3.3% is found. Both datasets show that the firm entry rate in Spain is declining over time; however, the magnitude of this change is relatively small for reported firm age in the CBI (CBI 2).

Figure 6(b) displays the corresponding exit rates. Once again, we find a substantially higher exit rate in the SocS data than in the U.S. The CBI exit rate is lower than the rate in SocS before 2020, however, it increases markedly towards the end of the sample period. This rise is most likely the result of some firms not continuously reporting in the

Table 2: Employment shares of exiting firms

Size	Social security	CBI	BDS
$E_{it} < 5$	37.25	13.70	23.27
$E_{it} < 20$	25.15	22.41	28.76
$19 > E_{it} < 100$	16.56	26.58	28.70
$99 > E_{it} < 500$	10.41	20.57	13.55
$499 > E_{it}$	10.63	16.74	5.72

Note: This table displays the employment shares across different firm size categories of exiting firms. Exit in SocS and CBI: Last year a firm reports positive employment. Exit in BDS: No employment in t and positive employment in $t-1$. For the SocS and BDS data, size is defined as size at the end of the previous period. For the CBI, size is based on median employment in a year.

CBI data, which, according to our definition, gets picked up as firm exit when we come closer to the end of the sample period.

Table 2 shows that firm exit is also tilted to large firms in the CBI compared to the SocS data. Almost 17% of employment of exiting firms is at those with more than 499 employees in the CBI compared to less than 11% in the SocS data. Part of this phenomenon is due to the CBI being tilted towards large firms. Yet, we find that the exit distribution is even more tilted in that direction than the overall firm-size distribution. Again, we believe that this issue is due to picking up as exiting firms those which do not continuously report to this dataset.

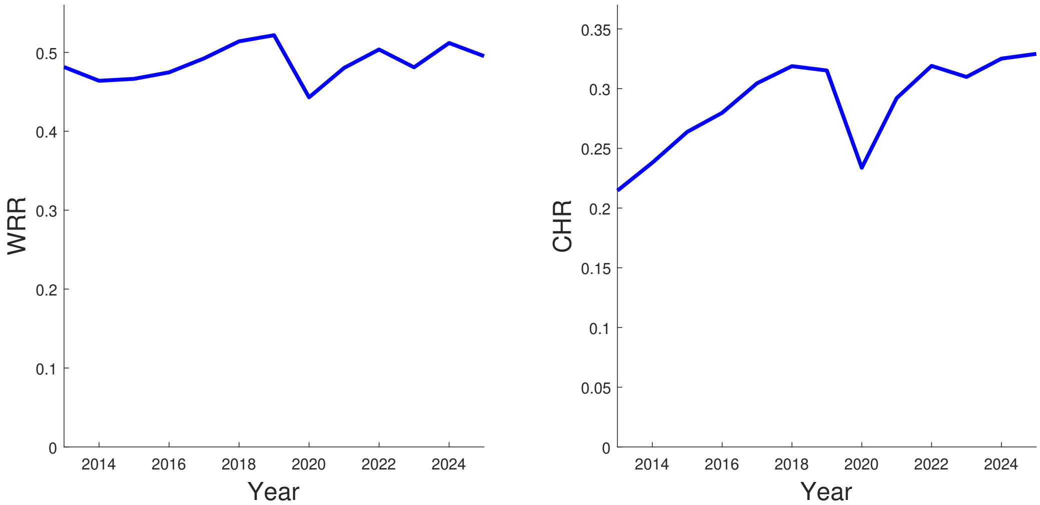
Comparing the exiting distribution in the SocS data with the BDS data shows that firm exit is more concentrated at very small and very large firms in Spain than in the U.S. Maybe surprisingly, the share of employment in Spain at very large exiting firms is almost twice as large.

3.5 Worker flows and the 2022 labor market reform

As already mentioned, in the first semester of 2022, a major labor market reform went into effect in Spain that drastically reduced the share of TC with less employment protection. As Figure 4(a) shows, despite the drop of the share of TC from 30% to less than 15%, the job reallocation rate hardly changed. Once more, this behavior is consistent with the above-mentioned argument by Pries and Rogerson (2005) about job reallocation being independent of labor market institutions. Instead, making it harder for firms to separate from workers should reduce worker reallocation. Note that, though the CBI does not allow us to compute worker reallocation, the SocS data does.

Following Davis, Faberman, and Haltiwanger (2012), we define a new hire as a worker who did not work for the firm in $t-1$ but is employed at year t, H_{it}. Similarly, we define a separation as a worker who was employed at a firm in $t-1$ and is no longer employed in t, S_{it}. We then compute the worker reallocation rate as $WRR_t = HR_t + SR_t - EGR_t$,

Figure 7: Worker flows in Spain



(a) Worker reallocation

(b) Worker churn

Note: This figure displays the worker reallocation and the churn rate over time using SocS data. The worker reallocation rate is defined as the sum of the hiring and separations rates net of the employment growth rate. The churn rate is defined as the sum of the hiring and separation rates net of the sum of the job creation and destruction rates.

where HR_t and SR_t are the hiring and separation rates. In addition, to account for the time trend in the job reallocation rate, we also compute the so-called churn rate as the worker flows in excess of job flows: $CHR_t = WRR_t - JRR_t$.

Figure 7 shows that, regardless of the measure being considered, the 2022 reform has not decreased worker turnover so far. Our finding for yearly worker turnover is consistent with Conde-Ruiz, García, Puch, and Ruiz (2025), who show that the reform did not affect daily worker flows. In contrast, Banco de España (2023) finds a drop from 1.33% to 1.12% in monthly worker turnover rates from 2015-2019 to 2022-2023. However, these results are difficult to compare to ours, as Banco de España (2023) reports monthly worker turnover rates that are inconsistently low compared to the worker turnover we find. To see this, note that $12 * WTR^{monthly} \geq WTR^{yearly}$ by definition, as the same worker can be hired and separated multiple times across months in the same year. Since we find an average yearly worker turnover rate of 52% with SocS data, the BdE monthly reported rates look implausibly low. Nonetheless, and consistent with our findings, BdE finds that worker turnover among employees with PC has increased after the 2022 reform, possibly because firms started dismissing these workers earlier than before to save upon firing costs which were on average higher after the ban of the project-based TC. Finally, we note that we cannot compare the Spanish data to U.S. data, as worker turnover at the yearly frequency is not available in publicly available data. However, Spanish worker turnover is certainly lower. For example, Abowd and Vilhuber (2011) report a quarterly worker turnover rate of 49%, which already almost matches the 52% yearly worker turnover in Spain.

4 Firm size

4.1 Firm size distribution

A large body of literature shows that more productive economies concentrate employment at large firms (see, e.g., Braguinsky, Branstetter, and Regateiro, 2011; Bento and Restuccia, 2017, 2021; Bachmann, Bayer, Stüber, and Wellschmied, 2026).[10] The top panel of Table 3 compares the employment shares at different firm sizes in Spain to the U.S. Two main findings stand out. First, Spain has substantially more employment at very small firms (<5 employees). The BDS data does not allow us to disaggregate the data yet further. However, when computing average firm size within that category, such a number is 2.2 for the U.S. and 1.53 for Spain. Put differently, even among this small firm-size category, Spain has more employment concentrated in the left tail than the U.S. Conversely, the latter has substantially more employment at very large firms, with more than 52% of workers operating at firms exceeding 500 workers against only 31% in Spain.

Comparing the CBI to the SocS data shows that the former captures well the middle of the firm-size distribution (5–500 employees). However, while it understates the prevalence of employment at very small firms, it overstates the prevalence at the largest firms, despite excluding financial firms.

Bento and Restuccia (2021) document that average firm size is larger in the manufacturing sector than in the overall economy. The bottom panel of Table 3 shows that the U.S. manufacturing size distribution is, indeed, shifted to the right compared to the overall economy. In Spain, average firm size is also substantially larger in the manufacturing sector (15.9 vs. 7.1). However, as Table 3 shows, unlike the U.S., larger firm size does not go hand-in-hand with an overall right shift of the firm size distribution. That is, the larger average firm size in Spanish manufacturing is mostly the result of less employment at the smallest firms. In contrast, in Spanish manufacturing, employment is less concentrated at the largest firms compared to the overall economy (22% vs 31%).

Matching employment concentration at the top of the distribution is an important target for the literature estimating productivity losses resulting from factor misallocation. Prominent examples using the manufacturing sector from the CBI and ORBIS-AMADEUS data for Spain are Gopinath et al. (2017) and García-Santana et al. (2020). Both find that capital misallocation increased in the years after the introduction of the Euro. Reassuringly, the CIB data matches the size distribution in the manufacturing sector reasonably well. Nonetheless, just as with the overall economy, it somewhat overstates the employment share at the largest firms.

[10] Beyond understanding countries' productivity levels, Ascari, Colciago, and Membretti (2026) show that understanding countries' size distribution is also important to understand the effects of monetary policy.

Table 3: Employment shares

Size	Social security	CBI	BDS
	Total economy		
$E_{it} < 5$	12.8	10.26	5.39
$E_{it} < 20$	18.89	17.70	11.85
$19 > E_{it} < 100$	20.59	19.58	16.28
$99 > E_{it} < 500$	17.03	16.15	13.83
$499 > E_{it}$	30.75	36.31	52.66
	Manufacturing		
$E_{it} < 5$	6.12	5.36	1.83
$E_{it} < 20$	17.38	16.17	6.95
$19 > E_{it} < 100$	28.87	26.37	15.94
$99 > E_{it} < 500$	25.69	24.77	18.27
$499 > E_{it}$	21.94	27.34	57.00

Note: This table displays the employment shares across different firm size categories. The top panel displays the total economy, and the bottom panel displays only the manufacturing sector. In the SocS data and BDS, size is defined as the weighted-average employment between the current and previous end-of-period employment. In the CBI, size is defined based on average yearly employment.

4.2 Who creates jobs

The idea that small businesses are the engine of job creation is one of the most repeated mantras among policy advocates. Indeed, Neumark, Wall, and Zhang (2011) find that net job creation mostly stems from small firms expanding their employment.[11] Figure 8 provides one way to visualize this fact. It shows the share of newly created (gross) jobs from different firm-size categories. The right panel shows that about 40% of total new jobs are created by businesses with fewer than 5 employees (including start-ups) in the U.S., making them the single-most dominant source of new jobs. The left panel shows that this pattern is even more pronounced in Spain, where about 50% of all new jobs result from firms with fewer than 5 employees. What is more, the role of the largest firms is very different across the two countries. In the U.S., firms with at least 500 employees contribute more than 30% of all new jobs, whereas in Spain, it is less than 15%.

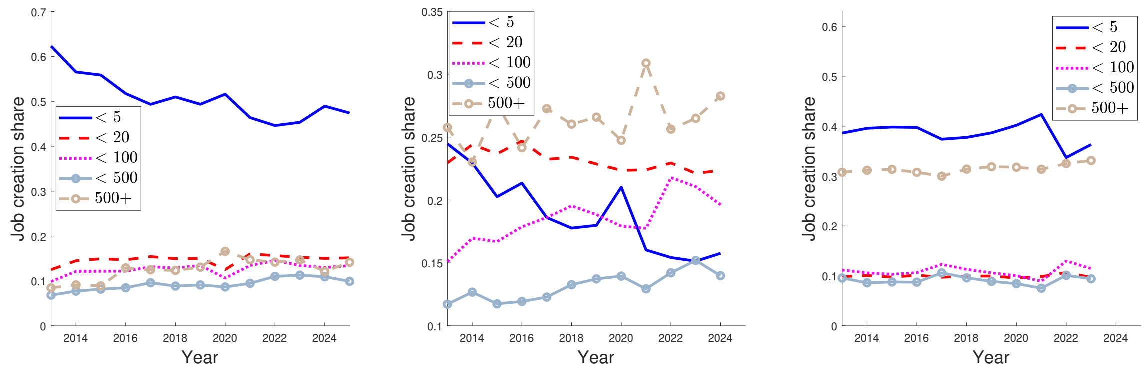
The central panel of Figure 8 shows that one would derive quite inaccurate conclusions about the importance of small firms for job creation in Spain from the CBI. Here, firms with fewer than 5 employees contribute only 15% of all new jobs. Instead, firms with at least 500 employees are the single largest job creators with about 27% of all new jobs.

4.3 Start-up employment growth

Recent studies have aimed at understanding cross-country differences in the cross-sectional size distribution through the dynamics of entering firms. A prominent example is Hsieh

[11] Haltiwanger, Jarmin, and Miranda (2013) show that most of the pattern is driven by firm age instead of size.

Figure 8: Job creation and firm size



(a) Social Security (b) CBI (c) BDS

Note: This figure displays the share of jobs created by different firm sizes. In the SocS and BDS data, firm size is defined as beginning-of-period employment. In the CBI, size is defined based on average yearly employment.

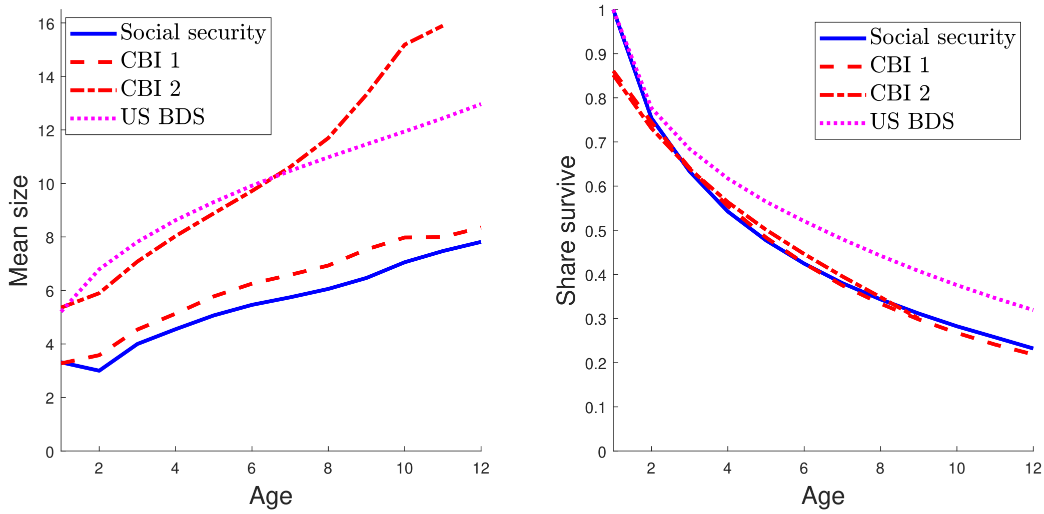
and Klenow (2014), who find that firms in Mexico and India grow much less than those in the U.S. They interpret start-ups' ability to grow into large firms as an indicator of their incentives to invest into productivity-enhancing technologies. Riveiro (2025) using the CBI, and Villegas-Sanchez (2025) using ORBIS-AMADEUS data show that firm growth is also much lower among Spanish compared to U.S. start-ups. Other studies using Spanish data to compute firms' life-cycle patterns include Budí-Ors (2025), who uses CBI data to find higher growth rates in large cities, and Guntin and Kochen (2025) who show that those firms becoming eventually large backload profits according to the ORBIS data.

We compute life-cycle moments for firm size and survival probabilities. In the SocS data, the maximum imputed age that can be observed is 12 years, and we restrict our analysis up to that age. To do so, for all age groups, we pool all the available years in the data. This approach is useful since we have a large number of observations, e.g., firms of age 3 are observed in several years. Note that, for this method to be meaningful, the firm distribution should be approximately stationary. To check whether this assumption is plausible, we have also computed moments by following the 2013 cohorts over time and find almost identical results.

More concretely, we compute the mean employment at each age as $\frac{\sum_t \sum_i E_{it}(h)}{\sum_t N_{it}(h)}$, where $N_{it}(h)$ is the number of firms in sample year t of age h. Moreover, we compute firm exit rates (and implied survival probabilities) by calculating the probability of exiting for every firm age as $\frac{\sum_t \sum_i exit_{it}(h)}{\sum_t N_{it}(h)}$, where $exit_{it}$ is a dummy that is one if the firm exits.

In the BDS, we only observe eight age categories, namely, 1, 2, 3, 4, 5, 6, $7-11$, and $12-16$. To compute mean employment at each age, we assume that the value for the category $7-11$ is representative for age 9 and that the value for the category $12-16$ is representative for age 14, and use cubic-spline interpolation to obtain the values for all

Figure 9: Firms' life-cycle patterns



(a) Employment (b) Number of firms

Note: The left panel of this figure displays average firms' employment size over age. See the notes of Figure 6 for the employment definitions. The right panel displays the survival probabilities over age. $CBI1$: Age according to founding year. $CBI2$: Age according to imputed age.

ages 7-12. Next, to compute survival probabilities, we first compute these up to age 6 and assume that survival probabilities are log-linear after age 1 to extrapolate the survival rates for ages 7-12.

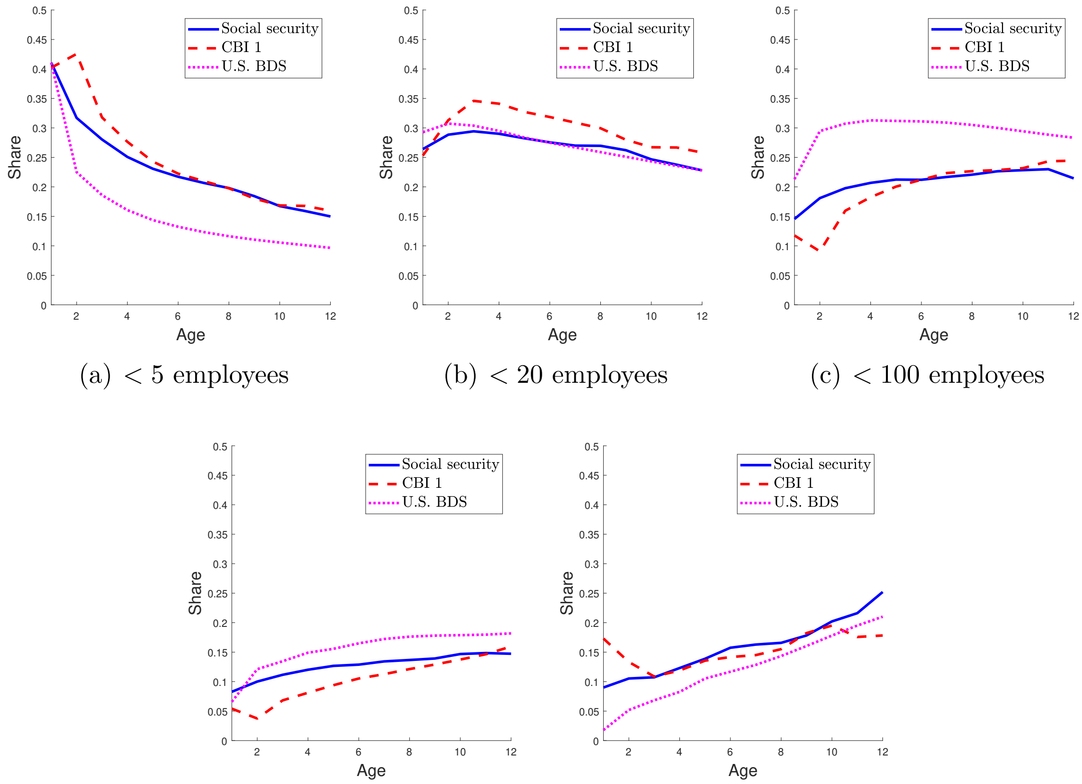
Figure 9(a) shows the results of this exercise. The average U.S. firm has about 1.9 more employees than the average Spanish firm in the SocS data at the end of its first year of life. What is more, U.S. start-ups grow faster over time. After 12 years, $E_{it} = 13$ in the U.S. but only 7.8 in Spain.

When using reported age, the life-cycle pattern of firms in the CBI is remarkably similar to firms in the SocS data. Still, firms are somewhat larger in the CBI even conditioning on age. When using as age definition that of a firm's first appearance in the data, the picture looks very different, and we discard it as a useful measure in the sequel.

Part of the observed employment growth in firms' age results from selection. Figure 9(b) illustrates this phenomenon in terms of the share of firms that survive up to a specific age. We find that survival rates are lower in Spain than in the U.S., where about 52% of an entering cohort is still active at age 6. In the SocS data, this fraction drops to only 42%. As regards Spain, the survival rate hazards are very similar in the SocS and CBI data.[12] We note, however, that survival rates are significantly lower than those found by López-García and Puente (2006) who relied on an earlier version of the CBI data for the end of the 1990s.

[12]By definition, all firms survive to age 2 in the SocS and BDS data given the end-of-period employment definitions. In the CBI, it is possible that firms report only in year one positive median-year employment.

Figure 10: Size shares over the life cycle



(a) <5 employees (b) <20 employees (c) <100 employees

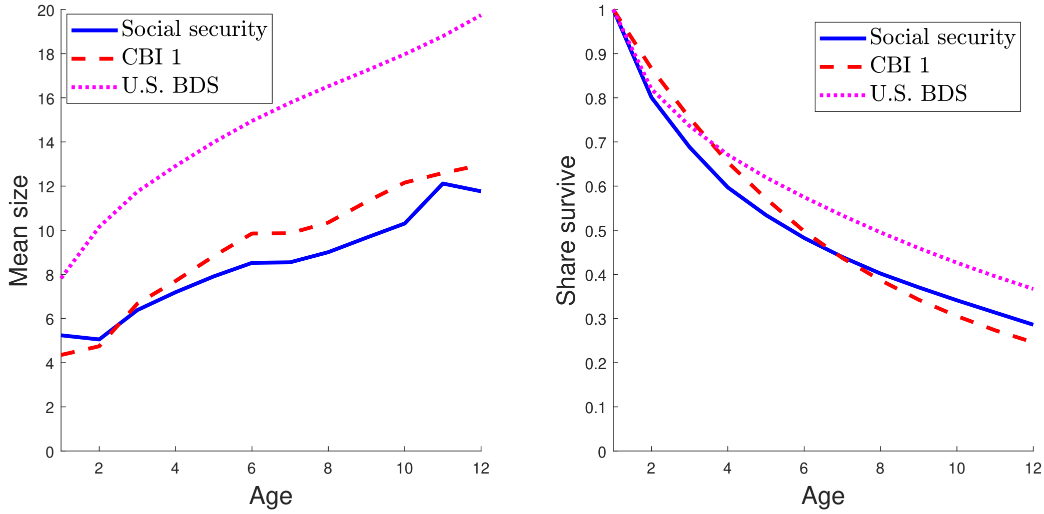
(d) <500 employees (e) >499 employees

Note: This figure displays the employment share of different firm-size categories over age. See the notes of Figure 6 for the employment definitions.

Sterk, Sedláček, and Pugsley (2021) highlight the role of some young firms experiencing tremendous employment growth–the so-called "gazelles"– in understanding the overall employment growth pattern of start-ups. In spite of not being able to follow individual firms in the BDS, we can analyze this phenomenon by computing employment shares by firm size category over the life-cycle. Panel (e) of Figure 10 shows that the employment share at firms with at least 500 employees is indeed growing rapidly with age. The share is less then 2% at birth and reaches 21% by age 12. Maybe surprisingly, this share is even higher in Spain during the first twelve years of firms' life cycles. The main underlying reason for this result is that a much higher share (7.6%) of employment is at those large firms already at entry. Unlike these very large firms, other Spanish firms exhibit much less life-cycle growth in the category of $100-499$ employees. Also noteworthy is the finding that the employment share of $20-99$ employee firms peaks at age 2 in the U.S. in stark contrast to peaking at age 11 in Spain.

Taken together, the following picture emerges to explaining the left shift of the Spanish firm-size distribution relative to the U.S. displayed in Table 3. First, the entry of very small firms is much more prevalent in Spain. Second, not enough Spanish start-ups

Figure 11: Life cycle in manufacturing



(a) Employment (b) Number of firms

Note: The left panel of this figure displays average firms' employment size in the manufacturing sector over age. See the notes of Figure 6 for the employment definitions. The right panel displays the survival probabilities in the manufacturing sector over age. $CBI1$: Age according to founding year. $CBI2$: Age according to imputed age.

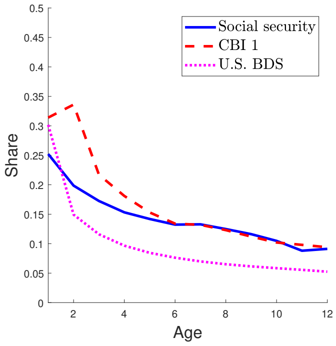
manage to grow into the size category of $100 - 499$ employees. Third, the survival of Spanish start-ups is very low, leading to the presence of many young, small firms.

Comparing the two Spanish data sets again, the CBI generally captures the employment share dynamics of entering firms. The most important difference arises at very large firms. While their employment share increases by 16 pp. in the SocS data between ages 1 and 12, it is basically flat in the CBI. Put differently, one would conclude incorrectly from the CBI that young firms fail to expand into this largest employment category when that is far from being the case with SocS data.

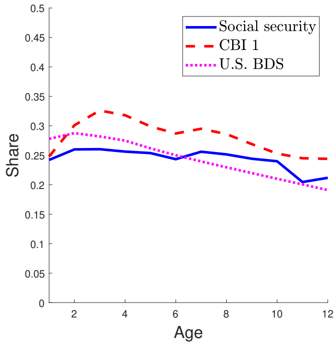
As regards the manufacturing sector, Table 3 shows that the firm-size distribution is particularly shifted to the left in Spain. This phenomenon can be understood with the help of Figure 11 that displays the behavior of start-up firms in this sector. The left panel shows that Spanish manufacturing start-ups perform rather poorly. At entry, their average size is about 2.6 employees lower than in the U.S. By age 12, this gap widens to 8 employees. The right panel, in turn, shows that the slower growth occurs despite lower survival rates, i.e., more selection. After 6 years, 57% of entrants are still operating in the U.S. against only 48% in Spain. In terms of average employment and survival rates, the CBI matches the SocS data well.

Figure 12 illustrates the lower employment growth again, but this time from the perspective of employment shares over the life-cycle. When comparing Spain to the U.S., one has to keep in mind that the BDS censors cells with too few observations, which affects very young, large firms in several years. In those instances, we assign zeroes to

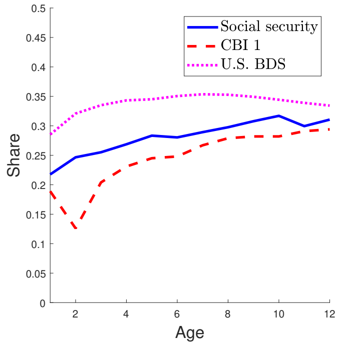
Figure 12: Size shares over the life cycle in manufacturing



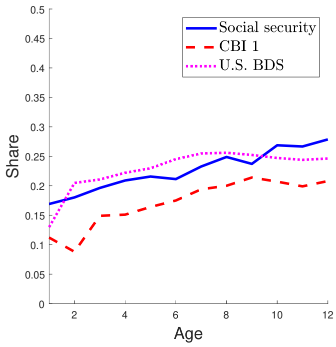
(a) < 5 employees



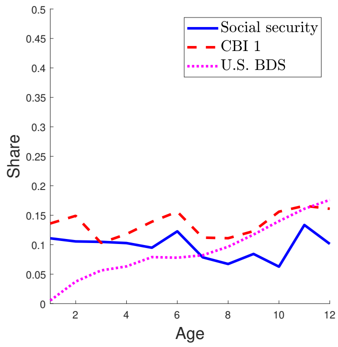
(b) < 20 employees



(c) < 100 employees



(d) < 500 employees



(e) > 499 employees

Note: This figure displays the employment share of different firm-size categories over age. See the notes of Figure 6 for the employment definitions.

missing values, which leads us to underestimate the level of those firms in the U.S. With that caveat in mind, the most striking feature is that the employment share of Spanish manufacturing firms with at least 500 employees is slightly *decreasing* over the life-cycle (from 11.1% at entry to 10.1% at age 12). In the U.S., by age 12, 17.6% of employment is in that category. In other words, the low employment share of Spanish manufacturing in the size category of at least 500 employees is closely linked with start-ups mostly failing to grow into that category. The CBI is able to capture the overall life-cycle dynamics; however, it systematically understates/overstates some employment shares.

5 Concluding remarks

Having got access to the universe of employees in Spain and the firms where they work by means of SocS records, allows us to argue that other datasets, like the CBI elaborated by the BdE, lacks enough representativeness to construct reliable job and worker reallocation rates and to analyze their cyclical behavior after the global financial crisis (2013-2024). Furthermore, we provide a comparison of the findings drawn from these datasets to the stylized facts in the U.S., obtained from its BDS dataset, to put Spain into perspective.

First, we show that cyclical fluctuations in dependent employment growth rates are more pronounced with the CBI data than with SocS data and that such a difference cannot be explained by the exclusion of the financial sector from the former but rather is due to the cyclicality of the number of firms covered by these data sources.

Second, job reallocation rates in the SocS dataset are higher than in the CBI, and are similar to those in the U.S due to the high turnover rate of temporary jobs, which are understated in CBI before the 2022 labor market reform in Spain. As relevant sources of job reallocation, we find that the CBI understates large employment adjustments by firms, including firm entry and exit.

Third, unlike the CBI the SocS data allows us to go beyond job flows and study worker flows. We show that worker reallocation is lower than in the U.S., and did not decline after the 2022 reform.

Fourth, regarding the firm size distribution, we find that the CBI understates the prevalence of employment at the lower tail of the distribution and overstates the upper tail, despite excluding financial firms. Similarly, with respect to job creation, CBI downplays the role of small firms. The SocS data attributes 50% of total new jobs to firms with fewer than 5 employees, while firms with at least 500 employees account for less than 15%, compared to 30% in the U.S.

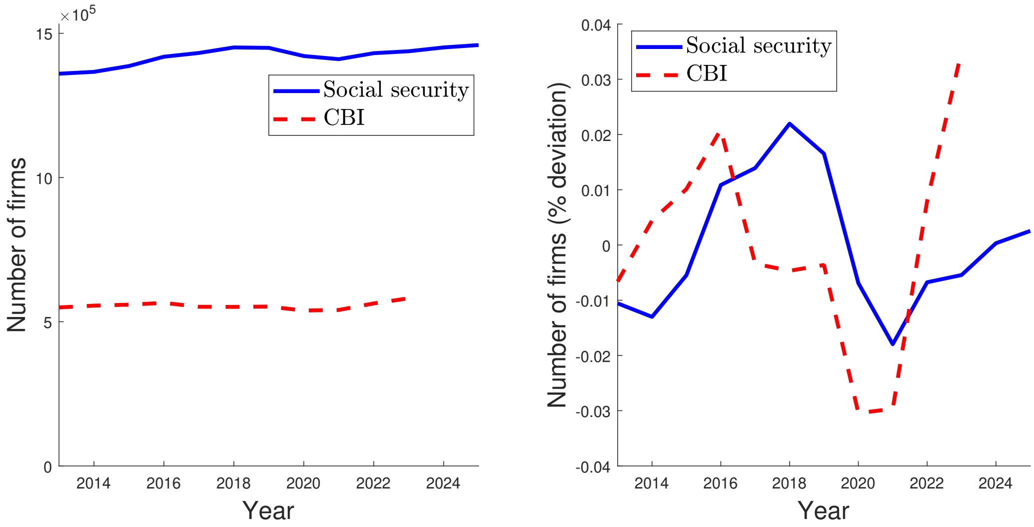
Finally, by computing life-cycle moments for firm size, as well as survival probabilities, we document a left shift of the Spanish firm-size distribution relative to the U.S. due to the higher entry of very small firms in Spain, lower survival probabilities of start-ups, and less employment growth among survivors. Moreover, these idiosyncratic features of Spanish firms are further accentuated in the manufacturing sector.

Overall, we claim that generalized access to the universe of SocS data offers many advantages over CBI data when analyzing labor market flows in Spain. Yet, efforts by the BdE in addressing selection biases in the CBI by merging its information with that of other statistical sources, like the SABI dataset, may be a step in the right direction.

A Number of firms

Figure A.1 compares moments of the number of firms in the SocS data to the CBI. The left panel displays the total number of firms over time. It shows that the CBI captures about 39 percent of all firms in Spain. The right panel displays the cyclical component from an HP-filter of the (log) number of firms. It shows that, in percentage deviations, the number of firms is more volatile in the CBI than in the SocS data.

Figure A.1: Number of firms



(a) Total (b) Cyclical component

Note: The left panel of this figure displays the total number of active firms. The right panel displays the HP-filtered (log) series with a smoothing parameter of 100.

Conflict of interest: The authors have no relevant non-financial interests to disclose.

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Data Availability The BDS data is publicly available here. The CIB data is only available with a research proposal from the BdE. The social security data is generally not publicly available. Researchers can, however, make a research proposal to get access. We provide the aggregate time series data for researchers on this site.

References

John M. Abowd and Lars Vilhuber. National estimates of gross employment and job flows from the quarterly workforce indicators with demographic and industry detail. *Journal of Econometrics*, 161(1):82–99, 2011.

Miguel Almunia, David Lopez Rodriguez, and Enrique Moral-Benito. Evaluating the macro-representativeness of a firm-level database: an application for the spanish economy. *Banco de España Ocassional Paper*, (1802), 2018.

Guido Ascari, Andrea Colciago, and Marco Membretti. The employment concentration channel of monetary policy. 2026.

Iván Auciello, Josep Pijoan-Mas, Pau Roldan, and Federico Tagliati. Dual labor markets in spain: A firm-side perspective. *Documentos ocasionales-Banco de España*, 10:1–25, 2023.

Rüdiger Bachmann, Christian Bayer, Heiko Stüber, and Felix Wellschmied. Monopsony makes firms not only small but also unproductive: Why east germany has not converged. *The Review of Economic Studies*, forthcoming, 2026.

Banco de España. The spanish labour market: current developments, structural trends and labour market policies. In Banco de España, editor, *Annual report*. Banco de España, Madrid, 2023.

Pedro Bento and Diego Restuccia. Misallocation, establishment size, and productivity. *American Economic Journal: Macroeconomics*, 9(3):267–303, 2017.

Pedro Bento and Diego Restuccia. On average establishment size across sectors and countries. *Journal of Monetary Economics*, 117:220–242, 2021.

Samuel Bentolila, Pierre Cahuc, Juan J. Dolado, and Thomas Le Barbanchon. Two-tier labour markets in the great recession: France versus Spain. *Economic Journal*, 122 (562):155–187, August 2012.

Serguey Braguinsky, Lee G Branstetter, and Andre Regateiro. The incredible shrinking portuguese firm. *NBER Working Paper No. 17265*, 2011.

Tomás Budí-Ors. The life-cycle of firms and the productivity advantages of large cities. *Working Paper*, 2025.

Carlos Carrillo-Tudela, Alex Clymo, Cristina La Fuente, Ludo Visschers, and David Zentler-Munro. Spanish labour market, mobility and labour shortages. *SERIEs*, 16(2): 257–296, 2025.

J Ignacio Conde-Ruiz, Manu García, Luis A Puch, and Jesús Ruiz. Reforming dual labor markets: "real" or "contractual" temporary rates? *Labour*, forthcoming, 2025.

James S Costain, Juan F Jimeno, and Carlos Thomas. Employment fluctuations in a dual labor market. 2010.

Steven J. Davis and John C. Haltiwanger. Gross job creation, gross job destruction, and employment reallocation. *Quarterly Journal of Economics*, 107(3):819–863, 1992.

Steven J. Davis, Jason R. Faberman, and John C. Haltiwanger. Labor market flows in the cross section and over time. *Journal of Monetary Economics*, 59(1):1–18, 2012.

Antonia Diaz, Juan J Dolado, Álvaro Jáñez, and Felix Wellschmied. Labor reallocation effects of furlough schemes: Evidence from two recessions in spain. *European Economic Review*, 171:104894, 2025.

Carlos Díaz Moreno and José E. Galdón-Sánchez. Job creation, job destruction and the dynamics of spanish firms. *Investigaciones Económicas*, 24(3):545–561, 2000.

Juan J. Dolado and Ramón Gomez-Salvador. Creación y destrucción de empleo en el sector privado manufacturero español: Un análisis descriptivo. *Investigaciones Económicas*, 19(3):371–394, 1995.

Ángel Estrada, Mario Izquierdo, and Pilar García Perea. *Los flujos de trabajadores en España: el impacto del empleo temporal*. Banco de España. Servicio de Estudios, 2002.

Alejandro Fernández Cerezo, Borja Fernández-Rosillo San Isidro, and Natividad Pérez Martín. The banco de españa's central balance sheet data office database: A regional perspective. *Banco de España Occasional Paper*, (2429), 2024.

Manuel García-Santana, Enrique Moral-Benito, Josep Pijoan-Mas, and Roberto Ramos. Growing like spain: 1995–2007. *International Economic Review*, 61(1):383–416, 2020.

Carlos García-Serrano and Miguel A Malo. Worker turnover, job turnover and collective bargaining in spain. *British Journal of Industrial Relations*, 40(1):69–85, 2002.

Gita Gopinath, Şebnem Kalemli-Özcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez. Capital allocation and productivity in south europe. *The Quarterly Journal of Economics*, 132(4):1915–1967, 2017.

Rafael Guntin and Federico Kochen. The origins of top firms. *Working Paper*, 2025.

John Haltiwanger. Job creation and firm dynamics in the united states. *Innovation policy and the economy*, 12(1):17–38, 2012.

John Haltiwanger, Ron Jarmin, and Javier Miranda. Business formation and dynamics by business age: Results from the new business dynamics statistics. *CES preliminary paper*, 18:2010, 2008.

John Haltiwanger, Ron Jarmin, and Javier Miranda. Where have all the young firms gone? *Business Dynamics Statistics Briefing*, 6, 2012.

John Haltiwanger, Ron S Jarmin, and Javier Miranda. Who creates jobs? small versus large versus young. *Review of Economics and Statistics*, 95(2):347–361, 2013.

Hugo Hopenhayn, Julian Neira, and Rish Singhania. From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share. *Econometrica*, 90(4):1879–1914, 2022.

Chang-Tai Hsieh and Peter J Klenow. The life cycle of plants in india and mexico. *The Quarterly Journal of Economics*, 129(3):1035–1084, 2014.

Yoonsoo Lee and Toshihiko Mukoyama. Entry and exit of manufacturing plants over the business cycle. *European Economic Review*, 77:20–27, 2015.

Paloma López-García and Sergio Puente. Business demography in spain: determinants of firm survival. *Banco de España Research Paper No. WP-0608*, 2006.

David Neumark, Brandon Wall, and Junfu Zhang. Do small businesses create more jobs? new evidence for the united states from the national establishment time series. *The Review of Economics and Statistics*, 93(1):16–29, 2011.

Patrizio Pagano and Fabiano Schivardi. Firm size distribution and growth. *Scandinavian Journal of Economics*, 105(2):255–274, 2003.

Josep Pijoan-Mas and Pau Roldan-Blanco. Dual labor markets and the equilibrium distribution of firms. *Working Paper*, 2024.

Michael Pries and Richard Rogerson. Hiring policies, labor market institutions, and labor market flows. *Journal of Political Economy*, 113(4):811–839, 2005.

Fernando Riveiro. Factor misallocation and high-growth firms. *Working Paper*, 2025.

Vincent Sterk, Petr Sedláček, and Benjamin Pugsley. The nature of firm growth. *American Economic Review*, 111(2):547–579, 2021.

Carolina Villegas-Sanchez. Business dynamism and the life cycle of firms: a firm-level analysis of spain. *SERIEs*, 16(2):297–320, 2025.