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HOW DO FIRMS USE FIXED-TERM CONTRACTS?

by Matteo Sartori*, Marco Guido Palladino** and Eliana Viviano*

Abstract

This paper examines how Italian firms use fixed-term contracts (FTCs) and documents the relative importance of seasonal needs, worker screening and buffer-stock motives. Using matched employer–employee data for 2013–2017 merged with firm-level balance-sheet information, we select a set of firms that systematically rely on temporary employment, generating over 85 per cent of its total volume. By focusing on these firms, we show that two *ex ante* contract features — the seasonal label and the initial duration — are highly informative about firms' hiring intentions. Use of seasonal contracts is limited and concentrated in a narrow set of sectors, while longer initial durations strongly predict conversion into permanent jobs, reflecting screening behaviour driven mainly by firm-specific factors. In contrast, most FTCs are short, non-seasonal and concentrated in firms dealing with lower productivity and higher revenue volatility, consistent with buffer-stock adjustment. A clustering exercise confirms that about 10 per cent of firms predominantly use seasonal contracts, one fourth use FTCs for screening, and roughly 65 per cent rely on them to manage uncertainty.

JEL Classification: J23, J41, J63, L23.

Keywords: fixed-term contracts, screening, contract conversions, seasonal workers, productivity.

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1. Introduction

Fixed-term contracts (FTCs) have become increasingly prevalent across many European countries — including Italy, Spain, France, and Germany — following their liberalization in the 1990s and early 2000s. In Italy, administrative data from the National Social Security Institute indicate that in 2024 approximately 60 percent of all hires were made under FTCs, while permanent hires accounted for only 15 percent, including job-to-job transitions.[1]

The expansion of FTCs has generated substantial policy debate. While they provide firms with flexibility in workforce management, workers who remain in temporary employment face greater income uncertainty and weaker career prospects. Assessing the trade-offs associated with FTCs therefore requires understanding both their consequences for workers and the reasons why firms rely on this form of employment.

The literature has made substantial progress on the first dimension, documenting the effects of temporary employment on workers' earnings and career trajectories (Booth, Francesconi, and Frank 2002; Filomena and Picchio 2022). By contrast, firms' motivations for using FTCs have been studied primarily in theoretical work, with limited empirical evidence. Abstracting from sporadic or one-off uses, previous research has identified three main motives underlying firms' systematic reliance on FTCs: coping with seasonal fluctuations in activity; screening workers prior to offering permanent jobs; and maintaining a flexible buffer of employment to adjust to economic uncertainty. However, little is known about the quantitative importance of these motives within a given economy — an assessment that is essential for policymakers seeking to design targeted and effective labor market interventions. Beyond the implications for workers' careers, the widespread use of FTCs is also potentially important for understanding Italy's long-standing productivity slowdown (e.g. Calligaris et al. 2018; Bugamelli et al. 2018), insofar as firms' hiring strategies affect human capital accumulation, worker retention, and the organization of production (Cappellari, Dell'Aringa, and Leonardi 2012).

The main contribution of this paper is to provide a detailed and comprehensive description of *how* firms employ FTCs in order to understand *why* they do resort to this

The views expressed in the paper are those of the authors only and do not involve the responsibility of the Bank of Italy, the Bank of France or the Eurosystem. We thank Bruno Anastasia, Federico Cingano, Giulio Mattioni and Roberto Torrini for helpful comments.

[1] The remaining 25 percent consist of apprenticeship, agency, and on-call contracts. We exclude these contract types from our analysis.

instrument in the first place. By identifying the motivation behind the use of temporary employment at the firm level, our analysis also allows us to assess which motive prevails at the macroeconomic level in Italy.

This paper examines the Italian labor market between 2013 and 2017, a particularly salient period for the study of temporary employment. According to Eurostat and the OECD, during these years the share of employees with a temporary job in Italy was about 11 percent, in line with the EU average and other major European economies (Figure C1). The stark discrepancy between the relatively modest share of workers employed on a fixed-term basis and the much larger share of FTCs observed in labor flows (60 percent) highlights a central feature of temporary employment in Italy: a high degree of contract turnover. Moreover, FTC regulation in Italy is relatively lax — particularly during the period we analyze — making this an ideal setting to analyze firms' choices concerning temporary employment in a context with limited statutory distortions.

Our main data source is the *Comunicazioni Obbligatorie* dataset, which records all dependent employment relationships in Italy and provides detailed anonymized information on workers, firms, and contract types. These data allow us to track each employment spell with precision, capturing its start date, initial and realized duration, and outcome. The available data cover the initial phase of the post–financial crisis recovery, up to mid 2019. We therefore focus on contracts signed between 2013 and 2017, which allows us to follow each contract for at least one year. From this source we construct two datasets that we use throughout the paper, one containing information on all worker-firm matches for which a FTC was used, the other featuring data on FTC utilization at the firm level. For the subset of incorporated companies, we are able to merge these data with firm-level balance-sheet information from CERVED, thereby including measures of revenues and productivity.

First, we examine the relationship between FTCs and seasonal employment. Italian legislation allows firms in selected sectors to use FTCs under a lighter regulatory regime if the job is seasonal. We show that seasonal FTCs are concentrated in specific months and that their use remains limited even among firms that are formally entitled to adopt them. In particular, by exploiting firm-level variation in the timing of temporary employment, we document substantial heterogeneity. While a small subset displays pronounced seasonal hiring, the majority spread FTCs relatively evenly over the year.

Second, we focus on FTCs as a screening device. Overall, just 21 percent of temporary worker-firm matches are converted to permanent positions. However, we document substantial heterogeneity in conversion rates across firms, only partly explained by observable worker and job characteristics. Instead, firm-specific factors account for a large share of the variation in conversion outcomes. This heterogeneity is reflected in contract design, as the initial duration of the contract — which is determined before the contract starts — emerges as a key predictor of subsequent stabilization. Matches for which the FTC has an initial duration of at least six months are significantly more likely to be converted into permanent positions. This evidence suggests that firms' conversion intentions are largely determined at the start of the employment relationship. Moreover, screening and seasonality emerge as distinct motives for the use of FTCs: firms with higher conversion rates make limited use of seasonal FTCs, and vice versa.

We then turn to the use of temporary employment as a buffer-stock. Buffer-stock motives emerge when firms use FTCs as a substitute for permanent jobs. Since buffer-stock motives cannot be directly identified at the contract level, we turn to test theoretical predictions of Cahuc, Charlot, and Malherbet (2016), that relate firms' overall intensity of fixed-term employment to their exposure to revenue volatility and their productivity. Consistent with the theory, we find a strong positive association between revenue variability and the use of temporary contracts. At the same time we show that firms using more FTCs have lower TFP and employ more often less educated workers.

To organize the evidence regarding different motives, we first check which share of worker-firm matches display strong signals of seasonal or screening use. A simple inspection reveals that about 10 percent of temporary employment relationships start with a seasonal FTC, while around 20 percent start with a FTC lasting at least 180 days. The remaining 70 percent of matches start with shorter and non-seasonal FTCs, and therefore cannot be unambiguously attributed to either screening or seasonal motives, but potentially constitute the group of firms using FTCs as a buffer-stock.[2]

Building on the descriptive evidence presented above, we then classify firms using six variables that directly describe FTC use: two different measures of employment seasonality; the within-firm average and standard deviation of contract duration for the first FTC in each match; one indicator measuring worker churn and another measuring employment fragmentation in temporary positions. Observations are assigned to clusters by running a k-means algorithm on the six variables without imposing *ex-ante* the number of clusters. The algorithm consistently identifies three clusters, which correspond to the prevalence of seasonal motives, screening motives, and buffer-stock motives. Genuinely seasonal firms amount to around 10 percent. Firms that use FTCs

[2] These results differ considerably from Colonna and Giupponi (2015) who rely on INPS sector-level data and conclude that seasonal contracts are one third of FTC in Italy. See footnote 20.

for buffer-stock purposes according to the k-means classification are around 65 percent, while one out of four firms use FTCs for screening.

All in all, our empirical analysis indicates that contract duration is a key margin to distinguish between motives behind the use of FTCs, as suggested by economic theory (Cahuc, Charlot, and Malherbet 2016). A declining levy on FTCs with respect to duration could induce firms to reduce their reliance on short-term arrangements, thereby decreasing their social costs in terms of turnover, income volatility, and lower human capital accumulation. Yet, raising the relative cost of FTCs may also dampen job creation, especially in some sectors and low productive firms. In particular, Cahuc et al. (2020) show for France that threshold-based taxation of FTC duration can produce perverse effects on both contract lengths and job creation, highlighting the importance of careful policy design. While Daruich, Di Addario, and Saggio (2023) do not find significant effects of fixed-term employment on firms' employment in Italy, this evidence does not rule out adverse effects in specific segments of the labor market or under alternative policy designs. The policy design should therefore balance efficiency gains against potential employment losses.

The paper is organized as follows. Section 2 briefly reviews the theoretical motivations behind firms' use of FTCs. Sections 3 and 4 describe the Italian institutional framework and the data. Section 5 presents the construction of our indices of FTC use. Section 6 documents the relative prevalence of each motive. Finally, Section 7 discusses the main findings, their policy implications and concludes.

2. Fixed-Term Contracts: A Short Theoretical Recap

Dual labor markets are characterized by the coexistence of two main types of employment contracts: standard open-ended contracts, by far the most common in developed countries and typically associated with firing costs; and fixed-term contracts (FTCs), used to regulate short-term employment relationships. Understanding the advantages, drawbacks, and trade-offs generated by this coexistence requires examining how firms actually use each contract type. The vast literature on the subject can be broadly grouped into two perspectives: frameworks that consider the two contract types as *complements*, addressing genuinely different needs; and those that regard temporary jobs as *substitutes* for permanent positions, with the choice mainly driven by their relative costs.

2.1. Fixed-Term Contracts as Complements to Permanent Jobs

If FTCs are viewed as complements to open-ended contracts, created with distinct objectives, their use is easy to rationalize. Three main scenarios fall into this class.

First, FTCs allow firms to adjust employment to seasonal fluctuations in economic activity. Given the cyclical nature and predictable duration of production activity in many sectors and locations, these contracts can be used to create short-term jobs that would otherwise not exist or be relegated to informal arrangements.

Second, temporary jobs can serve as screening devices. As with probationary periods, FTCs offer a time window during which firms and workers can learn about match quality. If the match proves valuable, the worker is converted to a permanent position. In practice, firms often prefer FTCs to probationary periods because separation costs are lower when a contract terminates due to expiration. This "stepping-stone" interpretation is formalized in Faccini (2014).

Finally, FTCs can be used for one-off jobs with a predetermined and well-specified duration. Examples include replacing absent employees or staffing a project with a clear end date. This leads to a sporadic use of FTCs by firms.

2.2. Fixed-Term Contracts as Substitutes for Permanent Positions

When FTCs are viewed as substitutes for open-ended contracts, the choice between the two revolves around a comparison of the surplus generated by each. In this perspective, temporary jobs function as an employment *buffer-stock*, allowing firms to preserve flexibility in the face of adverse demand shocks.

As Bentolila, Dolado, and Jimeno (2020) emphasize, however, this raises a fundamental question: why would firms ever offer permanent jobs if FTCs are available? From the firm's standpoint, a convertible FTC resembles a (European) put option on employment, which can be exercised in the event of a negative labor demand shock. In the presence of firing costs for open-ended contracts, this option carries value; and if search costs are sufficiently low, firms would have an incentive to cycle through FTCs rather than creating permanent positions (Blanchard and Landier 2002). Thus, the central challenge for theories where contracts are substitutable has been to explain their observed coexistence.

The most straightforward explanation assumes that firms would rely exclusively on temporary jobs if unconstrained, but that regulations limit their use (Cahuc and

Postel-Vinay 2002), as is the case in many countries.[3]

A second line of reasoning posits the existence of an exogenous productivity premium associated with permanent workers (Cabrales and Hopenhayn 1997; Caggese and Cuñat 2008). While analytically convenient, this explanation is difficult to validate empirically. Indeed, observed productivity (or wage) differences between permanent and temporary workers may not reflect ex-ante worker characteristics, but rather the consequences of contract assignment itself: permanent workers may develop higher productivity through human capital accumulation (i.e., learning on the job) or appear more productive due to selection effects (i.e., only the best performing temporary workers are retained and converted). Moreover, this approach neglects endogenous worker responses, as temporary employees may increase effort to enhance their chances of securing a permanent position (Engellandt and Riphahn 2005).

A third explanation stresses differences in job-filling speeds (Berton and Garibaldi 2012). In a setting with matching frictions and directed search, free entry into each sub-market leads to faster hiring for permanent positions, owing to workers' preference for job stability. Firms therefore face a trade-off between hiring speed and termination flexibility.

The most comprehensive account, however, is offered by Cahuc, Charlot, and Malherbet (2016). In their framework, firms and workers share the surplus from each job and choose the contract type based on the expected duration of random production shocks affecting that position. In equilibrium, jobs with low exposure to shocks are created as permanent contracts, especially when firing costs are modest; jobs with intermediate exposure begin as FTCs and are converted if no shock occurs; and highly exposed jobs are only offered on a temporary basis. This model is both parsimonious and powerful: it explains the coexistence of different contract types, and it elegantly rationalizes firms' decisions regarding contract characteristics and conversions from temporary to permanent positions.

3. Institutional Background

In Italy, as in many other European countries, the most common way to establish an employment relationship is through a permanent (or *open-ended*) contract, which binds the worker and the firm for an indefinite period of time. Typically, if a firm wishes to terminate a permanent contract, it must pay firing costs. Over the past thirty years,

[3] In Italy, fixed-term positions are capped at 20 percent of permanent jobs in most sectors.

however, European labor markets have been characterized by a growing recourse to *fixed-term* contracts. These contracts establish an employment relationship for a limited, predetermined period of time. When the contract expires, the associated separation cost (if any) is typically smaller than the one associated with permanent employment contracts (the so-called flexibility at the margin).

In the Italian legislation, the standard FTC (*Contratto a tempo determinato*) shares its essential characteristics with FTCs used in other European countries: *i*) it has a pre-determined duration; *ii*) it can be prolonged at the end of its term and it can also be renewed, albeit with some restrictions; *iii*) its total duration – including extensions – cannot exceed a certain threshold (24 months from 2012 to 2014; 36 months from 2015 to 2018); *iv*) it can be converted into an open-ended contract at any time before the end of the contract or during an extension. Last, in Italy no separation costs arise from an expiring FTC, whereas firing costs are traditionally high for permanent positions (Sestito and Viviano 2018).

The absence of stringent requirements for creating FTCs,[4] combined with the possibility of extending temporary employment for a relatively long period, has made Italy one of the European countries with the most flexible regulation of temporary jobs. This was particularly true between 2013 and 2017, the period considered in this paper.[5] Moreover, firms in sectors characterized by high seasonality face even less stringent conditions when hiring temporary workers. For instance, no limit applies to the share of total employees that can be hired with a seasonal FTC; seasonal contracts are not subject to the so-called *stop-and-go* discipline, i.e., mandatory cooling-off periods before a contract can be renewed; and when a 2018 reform reintroduced the requirement of a justification for any FTC renewal, seasonal FTCs were exempted from the provision. Jobs eligible for seasonal FTCs are identified through a list of occupations (D.P.R. 1963, n. 1525) and by collective bargaining agreements. Thanks to these features, FTCs are by far the most widely used institutional tool to formalize temporary employment spells[6] and represent the most common type of contract for workers in their first job (Di Porto and Tealdi 2024).

Given this legal framework, the cost of using a FTC to create a new job was negligible

[4]A clause requiring employers to provide explicit justification for temporary employment spells exceeding 12 months has been introduced and removed multiple times, but was mostly absent during our observation period (see Appendix A1).

[5]In August 2018, a reform (the so-called *Dignity Decree*) introduced new restrictions on the repeated and prolonged use of FTCs, which were fully implemented in 2019. In the years following the Covid crisis, the regulation of FTCs was once again liberalized.

[6]Other types of temporary employment include *project-* or *task-based* contracts, and *casual* work.

between 2013 and 2017 and Italian firms thus enjoyed considerable freedom in managing their workforce, making Italy's labor market an ideal setting to study the drivers of temporary employment. Further details on the legislation of FTCs in Italy during the period that we analyze can be found in Appendix A1.

Last, two notes of caution are warranted. The first concerns cost comparisons: while separation costs are substantially lower for temporary jobs, the difference in per-period cost between the two contract types remains ambiguous. On one side, the supplementary unemployment insurance contribution (*contributo addizionale NASpI*) raises the cost of FTCs and is only partly recovered upon conversion. On the other, a firm can avoid the tenure-based wage increments (*scatti di anzianità*) by replacing temporary workers with new hires, although this forfeits the firm-specific training and match capital embodied in the incumbent. Because these forces operate in opposite directions, the net per-period cost differential between FTCs and permanent contracts is not unambiguously signed.

The second regards the interpretation of conversion rates over the period under study. Between 2015 and part of 2016, Italy introduced generous hiring subsidies for permanent contracts, which substantially reduced the cost of stabilizing temporary workers. To the extent that these policies encouraged conversions independently of firms' underlying screening intentions, the conversion probabilities observed in our data may overstate those that would prevail in the absence of such incentives (Sestito and Viviano 2018).

4. Data

4.1. Sources

The main data source for this paper is the SISCO database (*Sistema Informativo Statistico delle Comunicazioni Obbligatorie*), managed by the Italian Ministry of Labor and Social Policy. This database is constructed on the basis of mandatory notices that public and private employers must submit to the Ministry every time some change in the employment status of a worker occurs[7]. This collection of notices is organized into a dataset where one entry corresponds to one uninterrupted employment spell between a worker

[7] SISCO provides exhaustive coverage of all dependent employment spells initiated in Italy after 2008, when telematic reporting of new jobs became compulsory. For more information on the database and its construction process: *Il sistema delle Comunicazioni Obbligatorie: uno strumento per l'analisi del mercato del lavoro*, 2010; *Il sistema informativo statistico delle Comunicazioni Obbligatorie SISCO*, 2014.

and a firm. Compared to other matched employer-employee datasets available in Italy, SISCO tracks workers' occupational trajectories with high precision: it records the exact date when any employment contract starts or is terminated, allowing for an accurate measurement of employment duration and of the time elapsing between one contract and another, even within the same firm. For FTCs also extensions and conversions are accurately reported. Furthermore, the database provides additional information concerning the sector of the firm, basic worker demographic characteristics, and the contractual details of the job (contract type, location, work schedule, occupation).

For incorporated companies only, it is possible to merge the SISCO database with firm-level yearly accounting data collected by the CERVED Group, a major European information provider and rating agency. We further complement the data with additional information on total firm workforce deriving from social security records provided by the Italian social security institute (INPS)[8]. The enriched CERVED-INPS dataset is used for three purposes: first, to measure firm size; second, to obtain a time-invariant measure of firm productivity, computed by averaging yearly total factor productivity estimates derived from the widely recognized Wooldridge (2009) methodology (value-added version); third, to measure the variability of revenues at the firm level.

4.2. Sample Selection and Data Construction

In our analyses we exclude *i*) employment spells in the agricultural, public (public administration and defense, education and health services) and domestic-work sectors; *ii*) employment spells where the worker's age is below 18 or above 65 at the time of hiring. Although the original data span from 2013 to the first half of 2019, the sample is further restricted to FTCs signed between 2013 and 2017, amounting to about 18 million observations.[9] This time interval is chosen on two grounds. First, it allows us to limit censoring issues: the fraction of worker-firm matches for which no separation or conversion date is observed for the last observed FTC – which are thus dropped from our sample – is less than 1 percent. Second, during this period temporary jobs regulation was relatively lax in Italy, making observed economic outcomes mostly the product of market incentives. Table B1 reports the number of contracts, firms, workers, and temporary employment relationships by starting year.

After this first selection, we construct two datasets. In the *Matches dataset* we collapse

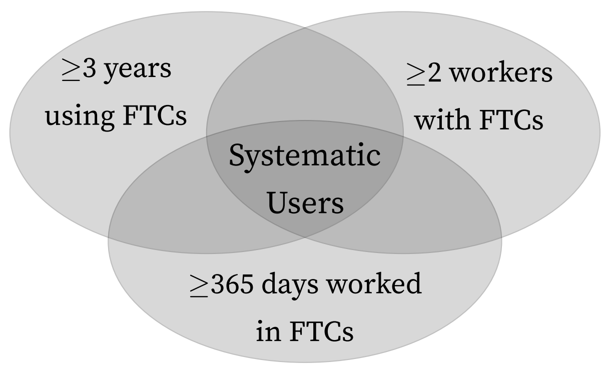
[8]The merge of the two data sources is performed based on the fiscal identification number of each firm, made available within a research project with ANPAL.

[9]Since internships are not formal employment contracts, the dataset does not include them.

all the observations (i.e. FTCs) referring to the same worker-firm pair to one entry. This new unit of observation, which we label as *match* (or *temporary employment relationship*), can represent either a single FTC or a sequence of them. This dataset covers all matches started using a FTC between 2013 and 2017 in the Italian private non-agricultural and non-domestic sector. Each entry in the dataset contains information on: *i*) the match as a whole (total employment days, number of separate FTCs); *ii*) the FTC that initiated it (starting date, *initial duration* – i.e. the duration stated by the contract at the start of the employment relationship); *iii*) its termination (ending date, separation or conversion outcome[10]).

The *Firms dataset* is instead structured as a cross-section at the firm level: each entry reports information concerning FTC utilization for a specific firm over the five-year window of interest, together with the information on firm size and productivity derived from the CERVED-INPS dataset (only available for a subset of observations).

FIGURE 1. Systematic Users Definition



We finally proceed with a further selection step for both datasets. Given the paper's objective of analyzing systematic patterns in FTC use, we focus on a subset of firms (and the corresponding set of matches), selecting employers that rely on temporary work in a recurrent way. Specifically, a firm is classified as a *systematic user* of FTCs if it simultaneously meets three criteria over the five-year observation window: (*i*) it employs temporary workers in at least three distinct calendar years; (*ii*) it employs at least two distinct individuals as temporary workers; and (*iii*) it generates at least 365 employment days in total across all temporary jobs (Figure 1). This definition ensures that we focus on firms for which temporary employment is a stable component of labor demand rather than a marginal or incidental one.

From 2013 to 2017 around 1.8 million firms are registered in the *Comunicazioni Obbligatorie* because of at least one hire or separation. Over 1 million firms used FTCs at least once between 2013 and 2017, most of them doing it every year (Table B2). Systematic

[10]Importantly, the dataset tracks both "direct" contract conversions (i.e. when the working relationship shifts from temporary to permanent with no gaps in employment) and "de facto" conversions (i.e. when a FTC terminates and a permanent contract is initiated between the same worker and firm within a short period of time, which we set at 365 days).

users constitute 42 percent of this group, but they generate the overwhelming majority of total temporary employment volume, driving its overall dynamics (86 percent of FTC workers and nearly 89 percent of FTC employment days; Table 1).

TABLE 1. Dataset Coverage

Sample	Firms		FTC Matches		FTC Workers		FTC Employment	
	N.	%	N.	%	N.	%	Days	%
All FTC users	1,044,453	100	8,032,179	100	5,251,752	100	1,956,862,302	100
Systematic FTC users	440,029	42.1	6,588,654	82.0	4,522,256	86.1	1,736,559,020	88.7
Systematic FTC users with CERVED match	226,981	21.7	4,693,673	58.4	3,456,844	65.8	1,261,165,394	64.4

Notes. Coverage of the samples described in section 4.2 in terms of firms, matches, workers and total employment days. Statistics regarding matches, workers and employment days only refer to temporary employees. The set of *systematic users* is the main sample of the paper, and it is used for most analyses.

An important consideration is that our definition of systematic users may select toward certain firm characteristics. A comparison of user types performed on full-sample firms with a CERVED-INPS match suggests that the sectoral composition of the two groups is rather similar (Table B3). Instead, systematic users are significantly larger than sporadic users (Table B4), and closer to the average size observed in other major EU countries, suggesting that, if anything, our firm-level analysis is based on a subset of more productive firms.

5. Types of Fixed-Term Contract Use

In this section, we characterize firms' use of FTCs by exploiting variation in contract characteristics and firm attributes. We focus on observable features of temporary matches — such as contract duration and seasonal status — and relate them to firm-level outcomes, including conversion rates, productivity, and demand volatility.

5.1. Seasonal Employment Adjustments

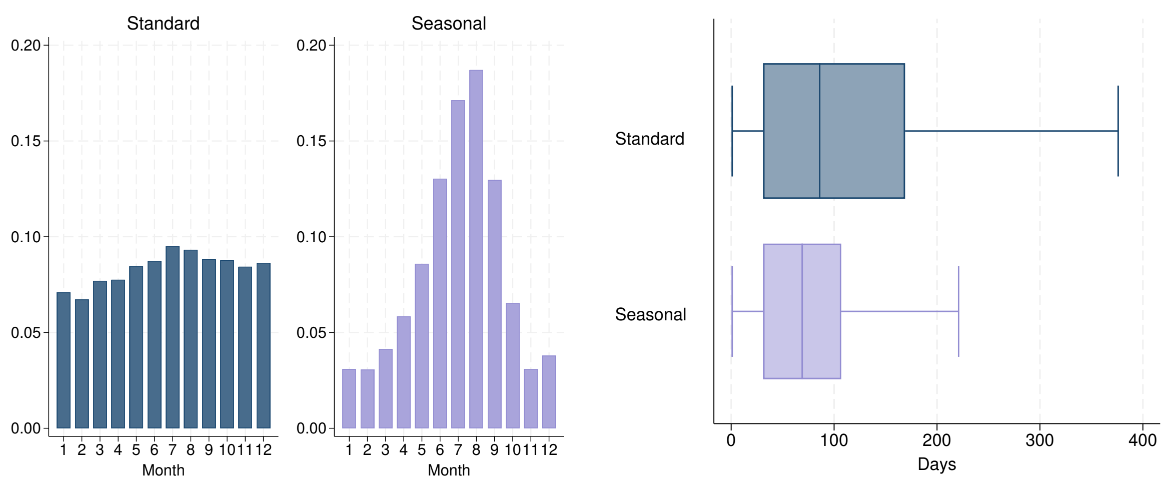
Seasonal fluctuations in activity generate swings in labor demand which are somewhat predictable and repetitive. The Italian legislation provides increased flexibility in FTC regulation for a restricted set of economic activities characterized by strong seasonal variability[11]. Firms in eligible sectors can flag a FTC as seasonal and thereby enjoy reduced regulatory constraints. This flag allows us to directly identify seasonality-driven temporary employment in our data.

Contract characteristics. Seasonal contracts are used intensively, when they are allowed. These contracts make up 67 percent of all FTCs among firms that have at least one seasonal contract. While standard FTCs are utilized throughout the year, the use of seasonal FTCs concentrates in summer months (Figure 2A), driven largely by tourism-related sectors (Figure C2A). The initial contract in a seasonal match tends to be shorter, lasting approximately between one and three months (Figure 2B).

FIGURE 2. Standard vs. Seasonal FTCs

A. Share of Total FTC Employment by Month

B. Stated Duration of the 1st FTC



Notes. The graphs compare standard and seasonal FTCs. Panel A: distribution of employment days by calendar month. Panel B: distribution of stated duration of the first contract in a temporary employment relationship.

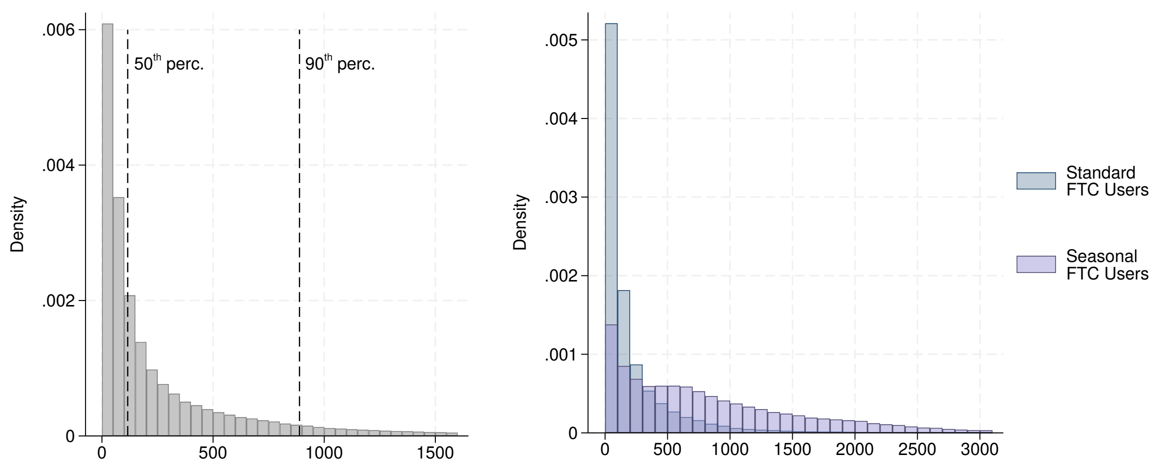
However, relying exclusively on the seasonal flag may overlook important sources of variation. While standard FTCs display, on average, a relatively uniform distribution over the calendar year, some firms that do not formally qualify for seasonal contracts may nevertheless face recurrent fluctuations in activity and address them through standard FTCs. To assess whether this is the case, we next shift from a match-level to a firm-level perspective and examine the extent to which firms' overall use of temporary employment exhibits seasonal patterns.

[11]The list of eligible activities was first provided in a 1963 Presidential Decree (DPR n. 1525/1963) and subsequently expanded by collective-bargaining agreements.

Firms' behavior. We introduce a novel firm-level measure of seasonality in temporary employment. Specifically, we measure firm-level seasonality by the use of a Herfindahl–Hirschman Index (HHI). For each firm, we compute the share of temporary employment (in days) occurring in each of the twelve calendar months – summing days across years for the same month – and then sum the squares of these shares. The normalized index ranges from 0 (perfect uniformity across all twelve months) to 10,000 (complete concentration in a single month). Values below 1,000 indicate an almost uniform use of temporary employment throughout the year, while values above 1,500 signal significant seasonality.

FIGURE 3. Firm-Level Seasonality: Employment Concentration Across Months

A. Overall Distribution B. By Seasonal Contract Use



Notes. Distribution of the seasonality index across firms. The normalized index is calculated at the firm level as $S = 10,000 * \frac{(\sum_{m=1}^{12} s_m^2) - \frac{1}{12}}{1 - \frac{1}{12}}$, where s_m represents the share of employment days generated by FTCs in total employment days in a given calendar month m (irrespective of the year). The number is normalized so that its distribution ranges from 0 to 10'000, as standard in the literature. Panel A: overall distribution. Panel B: separate distributions for firms using only standard FTCs and firms using seasonal FTCs at least once during our observation windows. See Rhoades (1993).

The pronounced right-skewness of the observed HHI distribution indicates that most firms spread their use of temporary employment relatively evenly across months (Figure 3A). For firms that use seasonal contracts at least once during our observation window the distribution has a fat right tail, signaling a strong seasonality, while firms that only resort to standard FTCs mostly display low concentration values.

The variability of the concentration index across firms can be formally decomposed using the law of total variance, checking what share of it is observed between- and within-groups defined at the province-sector level. The interaction of sector and location explains a non-negligible share of the overall variability, equal to 37 percent.

5.2. Screening Workers

Firms can use FTCs as screening tools, initiating most new employment relationships through them and converting only the best matches to permanent positions. Between 2013 and 2017, 21 percent of temporary matches in Italy were converted into open-ended contracts; three quarters of these conversions occurred without an interruption in employment. This match conversion rate corresponds to 10 percent of all FTCs being converted, a rate close to that reported by Güell and Petrongolo (2007) for Spain. Converted matches account for 35 percent of all temporary employment days (Figure C3).

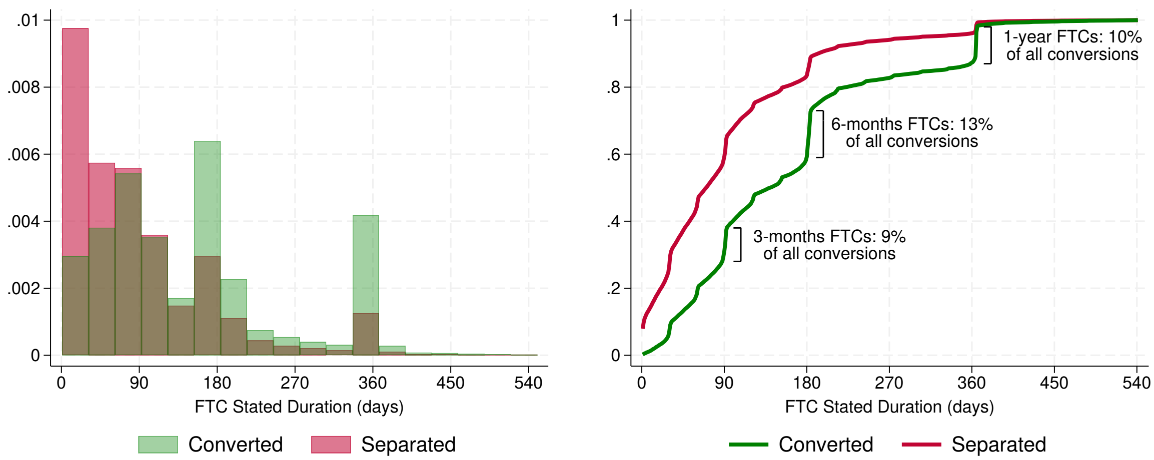
Contract characteristics. If firms use FTCs for screening purposes, these contracts should last long enough to allow firms to evaluate the productivity of the match with the worker. There are two main margins of adjustment for firms in this sense: the duration of the initial FTC; and the number of (separate) FTCs used to regulate the match. The data show that the large majority of temporary matches involve just one FTC (Figure C4A).[12] Consistent with the findings of Gagliarducci (2005), the likelihood of being offered a permanent job steadily decreases with the fragmentation of the temporary employment period (Figure C4B). However, the very low share of matches featuring three or more FTCs means that variation in the number of contracts contributes little to explaining conversion rates.

[12] Although recalls generate a large share of flows into employment (Charlot, Malherbet, and Menestrier 2024), they involve less than 20 percent of all temporary matches in our data.

FIGURE 4. FTC Duration and Conversions

A. Initial Duration Distribution
1st FTC for Each Match

B. Initial Duration C.D.F.
1st FTC for Each Match



Notes. Panel A: histogram of the initial duration for the FTC starting the employment relationship, by conversion outcome. Panel B: cumulative distribution function of the initial duration for the FTC starting the employment relationship, by conversion outcome.

By contrast, the duration of the first employment spell within a match — which, in light of the considerations above, typically coincides with the only spell — is a strong predictor of subsequent stabilization. The duration of this first spell is defined as the sum of the contract length defined at the start of the relationship (the *initial duration*) plus any subsequent contract extension.[13] Converted matches usually start with a much longer initial duration than non-converted ones, with pronounced mass points at specific contract lengths (Figure 4A). In particular, contracts with an initial duration of three, six, or twelve months account for approximately one third of all conversions (Figure 4B). These durations correspond to commonly used administrative horizons, which facilitate the accounting of wages and social security contributions. Moreover, conversion probabilities increase markedly when firms extend the first employment spell beyond its initial duration (Figure C5).[14] Since the initial duration of the first contract is determined *ex-ante*, it provides an informative signal of firms' hiring intentions: longer FTCs are more likely to reflect screening strategies aimed at potential permanent hires.

[13]An *extension* is defined as an agreement between the firm and the worker to prolong the employment spell beyond the original expiration date of the contract, with all other contractual terms remaining unchanged and no interruption in employment (in contrast to a *recall*). Figure C10 reports the distribution of total match duration by the duration of the first FTC.

[14]In particular, conversion rates peak when firms make use of the maximum number of legally permitted extensions — five during our analysis period — suggesting a systematic exploitation of the full regulatory margin prior to offering a permanent contract.

Beyond individual contract characteristics, conversion rates exhibit substantial heterogeneity across a wide range of market segments. Conversion rates vary substantially by sector – from nearly zero in film and television to above 50 percent in manufacturing, transport, and financial services (Figure C6A) – and even more by occupation, with service and sales jobs well below technical, clerical, and engineering roles (Figure C6B). Geographic and aggregate temporal patterns are modest, with a slight north–south gradient (Figure C7) and stable rates over time (Camussi, Colonna, and Modena 2022), except for a temporary rise in 2015–2016 linked to hiring subsidies for permanent contracts (Figure C8). Individual factors matter little, though young, older, and female workers have somewhat lower conversion chances (Figure C9). To understand how these factors interact, we next examine their joint contribution to explaining conversion rate variability. Using the *Matches dataset*, we estimate a series of linear probability models where a dummy variable indicating whether the firm-worker match is eventually converted to permanent is regressed on different sets of fixed effects. Our richest specification is:

$$y_i = \sigma_s + \pi_p + \tau_t + \phi_f + \omega_o + \alpha_w + \epsilon_i \tag{1}$$

where y_i is the conversion dummy for worker-firm match i and the parameters represent sector, province, time (year and month), firm, occupation and worker-profile fixed effects. Worker profiles are defined as sex×education×age cells.[15] We interpret the fitted values $\hat{y}_i$ as the predicted probability of conversion of a temporary job i for a given choice of fixed effects. For each of the Greek-letter factors, we run two regressions: one in which the corresponding fixed effect is included as the only covariate, and another one where it is the only one to be excluded. Comparing the share of variability in conversion rates explained by different sets of fixed effects provides insight into the relative importance of underlying factors in predicting conversion probabilities.

[15]Thanks to our large sample, all 288 possible combinations ($2 \times 3 \times 48$) are included in the regressions.

TABLE 2. Conversion Predictors

	R^2		
Fixed Effect	Single FE	All but one	All FEs
Sector	0.09	0.27	
Province	0.02	0.27	
Year	0.01	0.26	
Month	0.01	0.27	0.27
Firm	0.25	0.12	
Occupation	0.08	0.27	
Sex-age-education	0.02	0.27	

Notes. This table reports adjusted R^2 from employment-relationship level regressions with different fixed effects specifications. Column (1) includes only the single fixed effect listed in each row. Column (2) includes all fixed effects except the one in that row. Column (3) includes all fixed effects simultaneously. Sample: systematic users, see Table 1. N = 6,633,915 (6,633,902 in specifications including worker-profile and occupation fixed effects), owing to singleton dropping in fixed-effects estimation.

Table 2 provides a transparent decomposition of the sources of heterogeneity in FTC conversion probabilities. When included in isolation, sectoral and occupational fixed effects explain a non-negligible share of the variation, reflecting persistent differences in production technologies and job characteristics. However, once all other dimensions are controlled for, their marginal contribution becomes negligible. By contrast, firm fixed effects alone account for roughly one quarter of the total variance in conversion outcomes, and their exclusion from the full specification leads to a sizable drop in explanatory power.[16] This pattern indicates that firms' conversion behavior is largely driven by unobserved, firm-specific factors rather than by observable worker characteristics or aggregate conditions. Importantly, the dominance of firm fixed effects is not mechanically driven by sorting between workers and firms, as the correlation between worker-profile and firm effects is low.[17]

Firms' behavior. The previous analyses showed that the conversion probability of FTCs has a strong firm-specific component. To complete the picture, we examine whether

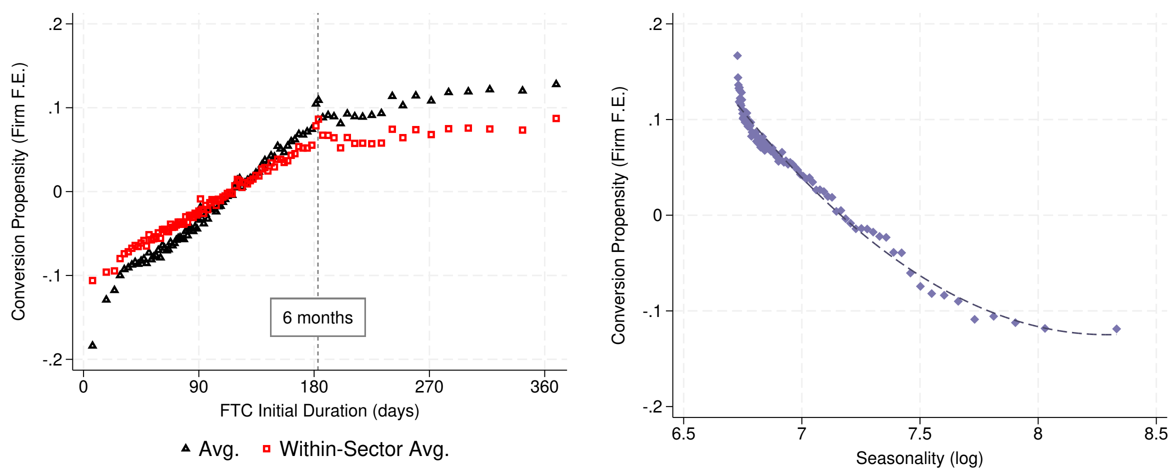
[16]Note that, for single-establishment firms, firm fixed effects subsume sector and province effects, which mechanically reduces the marginal contribution of the latter in specifications that include firm effects. Therefore, the residual explanatory power of sector and province fixed effects in the full specification reflects variation attributable to multi-establishment firms.

[17]Analysis available upon request.

firms' conversion propensity is signaled by their choices concerning the most important feature of FTCs: their initial duration. The binned scatter-plots in Figure 5A represent the conditional expectation of firm-level conversion rates – measured by the firm fixed effect estimated with the richest specification of Equation (1) – against one hundred bins in the distribution of average FTC initial duration across firms.[18]

FIGURE 5. Conversions, Duration, and Seasonality: Firm-Level Relationship

A. Conversion Propensity vs. Initial FTC Duration B. Conversion Propensity vs. Seasonality



Notes. Panel A: conditional expectation of firms' conversion propensity given the average FTC initial duration for new temporary employment relationships. Panel B: conditional expectation of firm conversion propensity given log-seasonality (normalized HHI of employment days across calendar months) at the firm level, focusing on firms with at least one seasonal FTC. Both graphs: conversion propensity is proxied by firm fixed effect estimated using the full specification in equation (1) .

The two variables display a strong positive correlation: firms that, on average, offer longer initial FTCs also exhibit a higher propensity to convert them into permanent positions. Importantly, this relationship flattens markedly at an average initial duration of about six months,[19] which is consistent with the inelastic response of conversions to contract duration beyond a given threshold documented by Kabátek, Liang, and Zheng (2023) for the Netherlands. The negligible increase in conversion propensity beyond this point suggests that, once the screening objective has been achieved, extending the duration of the temporary contract yields little additional information about match quality on average.

[18]Figure C11 plots the relationship at the sector level.

[19]This threshold does not reflect a particular institutional feature or policy; it was also present in 2013–14, before hiring subsidies for permanent contracts were introduced, and is therefore not a result of the incentive regime introduced in 2015–16 (see Appendix A1)

5.3. Buffer-Stocks

When FTCs are used as a substitute for open-ended positions, they essentially constitute an employment *buffer-stock*: a pool of workers that can be easily dismissed as a hedge against downside risks.

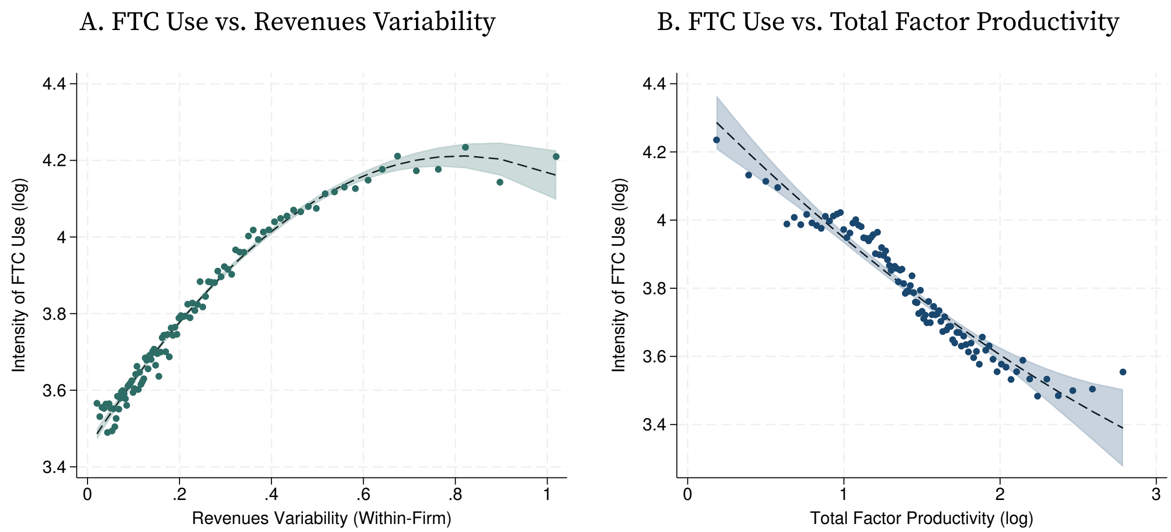
Buffer-stock behavior cannot be identified either directly or indirectly through contract characteristics. Unlike seasonality, there is no administrative indicator capturing this specific motive. Moreover, for a given contract initial duration, non-conversion may reflect either a screening process that revealed a poor match or a buffer-stock position where permanent hiring was never intended. We therefore adopt a different strategy to study buffer-stock behavior: we derive testable predictions from the theoretical framework of Cahuc, Charlot, and Malherbet (2016), the workhorse model of labor contract choice under uncertainty, and assess whether the empirical patterns are more consistent with buffer-stock or screening motives.

In the model, firms create jobs to exploit production opportunities and optimally match contract types to them based on their expected duration: stable, long-lasting opportunities are staffed with permanent jobs, while unstable, short-lived opportunities are staffed with temporary employees. In equilibrium, firms strike a balance between the risks of committing to a permanent contract and the costs of continuous re-staffing associated with temporary positions.

This framework generates several testable predictions. First, firms facing greater demand volatility – where production opportunities are on average shorter-lived – should exhibit higher temporary employment use. Second, higher productivity should be associated with longer FTCs, higher conversion rates, and a larger share of permanent employment, as the surplus generated by stable matches increases. Third, stronger reliance on complex knowledge and skills (*human capital*) should induce lower worker turnover, as firms facing high training costs for each new employee find it optimal to preserve valuable matches. Fourth, firms using FTCs primarily for seasonal needs – where opportunity durations are predictable rather than uncertain – should not exhibit these patterns. We next examine these predictions empirically, focusing on firm-level characteristics, as contract-level information alone is insufficient to disentangle buffer-stock behavior from screening motives.

First, we check the association between reliance on temporary employment and variability in firm revenues. We measure the former as the ratio between the sum of the employment days generated by all FTCs in a firm and total firm employment (Figure C12A); the latter by taking the coefficient of variation for firm revenues across our observation window. The two variables are strongly associated: a 0.5 increase in revenue variability — corresponding to a shift between the tenth and the ninetieth percentile — predicts a 65 percent increase in FTC intensity (Figure 6A); the relationship flattens out at very high variability values. The regression coefficient is estimated with very small robust standard errors.

FIGURE 6. Predictors of FTC Use



Notes. Panel A: conditional expectation of the intensity of FTC use given the variability of firm revenues (coefficient of variation calculated across years). Panel B: conditional expectation of the intensity of FTC use given firm productivity (total factor productivity, estimated using value added and total labor costs). Both panels: the conditional expectation is computed across 100 bins in the conditioning variable distribution, with no additional controls; the best-fit line is quadratic and standard errors are computed using 1000 bootstrap iterations; firms in the bottom and top 1 percent of the conditioning variable are not represented for better visual rendering. The intensity of FTC use is measured as the firm-level average of total days worked in fixed-term contracts divided by the total number of employees.
Source: authors' processing of data from *SISCO*, systematic users + CERVED sample; see Section 4.

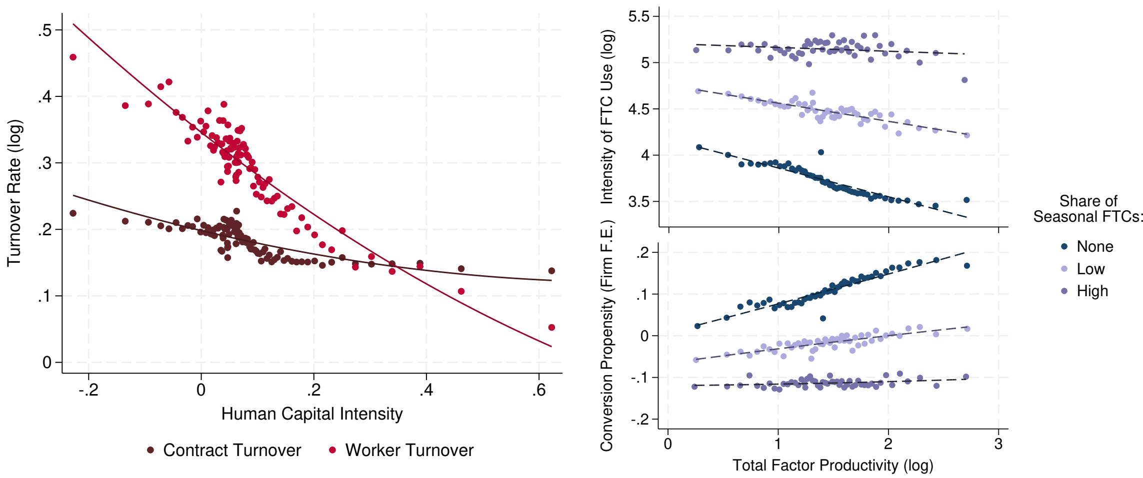
Second, the negative association between productivity and FTC intensity predicted by the model is also supported by the data (Figure 6B). The most productive firms tend to rely less on temporary jobs, especially when their revenues are not extremely volatile (Table B5).

Third, in the Cahuc, Charlot, and Malherbet (2016) model, contracting costs capture all costs associated with initiating a new employment relationship, including search, administrative procedures, and firm-specific training. These costs are incurred whenever firms replace an expiring FTC by hiring a new worker, but are largely avoided when the same worker is retained through contract renewals. As a result, human capital requirements are expected to negatively affect worker turnover more strongly than contract turnover. Figure 7A provides evidence consistent with this prediction (after controlling for firm sector). As firms' human capital intensity — proxied by the share of university graduates among employees — increases, the number of distinct temporary workers needed to generate a given amount of temporary employment declines sharply. By contrast, the number of FTCs per worker decreases much more gradually. This divergence indicates that firms with higher human capital requirements rely less on frequent worker replacement, while still making use of temporary employment through longer spells or repeated recalls of the same individuals.

FIGURE 7. Human Capital and Seasonality in Buffer Stock Use

A. Worker and Contract Turnover vs. Human Capital Requirements

B. Seasonality as a Mediator: FTC Use and Conversions



Notes. Panel A: conditional expectation of worker turnover (log of the number of temporary workers needed to generate 365 employment days) and contract turnover (log of the number of FTCs per temporary worker) as a function of firm-level human capital intensity (share of university graduates among workers), controlling for TFP and including six-digits sector fixed effects; sector variability in worker turnover is visible in Figure C13. Panel B: conditional expectation of FTC intensity (temporary employment days per employee, upper graph) and propensity to convert (fixed effects from the richest specification of Equation (1), lower graph) as a function of total factor productivity. Firms in the first group use only standard FTCs; firms in the second group display a below-median share of seasonal FTCs (conditional on using at least one); firms in the third group display an above-median share of seasonal FTCs (conditional on using at least one).

Last, given that seasonal use of FTCs is driven by predictable and somewhat regular swings in economic activity, uncertainty should not play a primary role in the dynamics of seasonal employment; accordingly, we do not analyze it. At the same time the links between FTC use and productivity predicted by the model should be attenuated for firms with a strong seasonal use. The latter implication is confirmed empirically. We split the sample into three groups of firms based on their reliance on seasonal FTCs. We find that as productivity grows, firms with no or few seasonal employees display lower reliance on temporary work and a higher propensity to convert; for firms with a strong seasonal component, on the contrary, no relationship emerges between productivity and FTC utilization (Figure 7B).

Together, these empirical patterns provide strong support for the model's predictions regarding temporary employment. While seasonal employment appears to be driven by distinct factors, screening and buffer-stock uses are systematically related to firms' productivity and exposure to uncertainty. One important consideration is worth making at this point. While our sample selection removes firms that resort to FTCs only occasionally, the residual category still places in the same basket two economically distinct types of firm: enterprises that face genuinely uncertain, fluctuating demand and use temporary workers as a buffer, and firms with a project-based business model, whose temporary hiring serves discrete tasks with a finite — and often foreseeable — horizon. The notion of "uncertainty" clearly differs across these cases, and the two are observationally equivalent in our data, since the ex-ante predictability of a task's end date is not recorded. What they share is a reliance on temporary work that is not concentrated in a few calendar months.

6. The Relative Incidence of Fixed-Term Contract Uses

The descriptive evidence presented so far suggests that two contract characteristics observable at the time of hiring — initial duration and seasonality — are informative about firms' motives for using FTCs. In this section, we exploit these dimensions to assess the relative importance of different uses of temporary employment and to document how prevalent buffer-stock behavior is among firms.

We proceed in two steps. First, we provide a simple, transparent classification of temporary employment relationships based on contract duration and the seasonal label. Second, we complement this approach with a firm-level classification obtained through machine-learning techniques that exploit a richer set of indicators.

6.1. A Simple Characterization of Temporary Employment Matches

FTCs are required to indicate whether they are motivated by seasonal needs and to state a contract duration at the start of the employment relationship. Because both pieces of information are determined ex-ante, they can be used to obtain a first-order classification of different uses of temporary employment. Treating the seasonal label as a proxy for seasonal use, and non-seasonal contracts with an initial duration of at least six months as indicative of screening, we obtain the subdivision of employment relationships reported in Table 3.

TABLE 3. Classification of Temporary Matches

	Seasonality		
Screening	Standard FTC	Seasonal FTC	Total
Duration < 180 days	5,516,237 (68.7 %)	783,489 (9.8 %)	6,299,726 (78.4 %)
Duration $\geq$ 180 days	1,670,845 (20.8 %)	61,608 (0.8 %)	1,732,453 (21.6 %)
Total	7,187,082 (89.5 %)	845,097 (10.5 %)	8,032,179 (100 %)

Notes. Number and share of matches based on the two key variables identifying seasonal use (seasonal label) and screening use (initial duration). Sample: matches involving systematic user firms, see Table 1.

About one tenth of all temporary matches start with a seasonal contract.[20] Consistent with both the theoretical framework and the descriptive evidence presented in the previous section, the share of matches that are seasonal and characterized by a long initial duration is negligible.

Turning to contract duration, 21.6 percent of temporary employment relationships start with an initial duration of at least six months. We focus on this threshold because the evidence in Figure 5A indicates that conversion propensities increase sharply up to this duration and display little additional variation thereafter. Using this cutoff, the table shows that long non-seasonal contracts account for a relatively limited share of total temporary matches, while the majority of employment relationships are characterized by short non-seasonal arrangements.

Taken together, the two proxies for seasonality and screening identify less than one third of total temporary employment. This suggests that most FTCs are not used as complements to permanent jobs: instead, they are likely exploited to retain flexibility,

[20]The share of seasonal contracts in our data is lower than that reported in INPS statistics. This difference partly reflects the fact that our analysis is conducted at the level of job matches rather than contracts. However, even when considering raw counts, the share of seasonal contracts among FTCs in the *Comunicazioni Obbligatorie* data cannot be directly compared with INPS records. Discrepancies arise from differences in the unit of analysis: CO notifications record each contractual communication separately, whereas INPS–Uniemens data aggregate employment at the weekly level. As a result, multiple CO notifications for the same worker within the same calendar week increase the total number of FTCs in the denominator, mechanically reducing the share of seasonal contracts.

consistent with buffer-stock use. In the next section, we refine this characterization by exploiting machine-learning techniques and a richer set of indicators drawn from theoretical predictions and from the empirical patterns documented above.

6.2. Classifying FTC-Using Firms Using Machine-Learning

The main limitation of the classification presented above lies in its reliance on a restricted set of variables describing contracts. Nonetheless, the analysis conducted in Sections 5.1 and 5.2 highlights that firm heterogeneity plays a crucial role in shaping the adoption of FTCs. Thus, to provide a more comprehensive characterization of firms according to their use of FTCs, we extend our previous analysis by focusing on firms instead of contracts and incorporating a richer set of variables.

We then run an unsupervised machine learning algorithm (k-means) to partition data into k clusters by iteratively assigning each data point to the nearest cluster centroid and updating the centroids based on the mean of assigned points until convergence is achieved (Steinley 2006). We iteratively run the algorithm for a number of clusters k going from 2 to 10 in order to find the optimal number of clusters.[21] The highest value of the Caliński–Harabasz index, a measure of cluster separation, is achieved for $k = 3$ (Figure C14). Three clusters also deliver stable estimates: despite not reaching its lowest value, the coefficient of variation across replications is 0.08 for $k = 3$, signaling very low variability across iterations in absolute terms.

The resulting partition is summarized in Table 4, while Table 5 reports summary statistics by cluster, separating clustering inputs from firm characteristics that are not used in the algorithm. Substantial heterogeneity emerges across groups. Cluster 1 includes about 10 percent of firms and is characterized by short contract durations, high seasonal concentration (HHI of 2,097 and a seasonal share of 72 percent), and high worker turnover, suggesting that temporary hiring mainly accommodates recurrent short-term needs.

TABLE 4. Cluster Composition

	Firms	Share
Cl. 1	44,247	10.1%
Cl. 2	110,649	25.1%
Cl. 3	285,133	64.8%
Total	440,029	100%

Cluster 2, which accounts for about 25 percent of firms, displays the highest average contract duration (250 days) and the highest duration variability, together with minimal seasonality and the lowest worker turnover rate. This group likely uses FTCs as a screen-

[21] We run the algorithm 100 times for each k and compute the average value for the Caliński–Harabasz Index (also known as Variance Ratio Criterion) and its variability across iterations.

ing device. Cluster 3 gathers the majority of firms (65 percent), showing intermediate contract lengths, low seasonality, and intermediate churning rates, consistent with buffer-stock motivations.

TABLE 5. Cluster Profiles

	Clustering inputs						*Other characteristics*			
	Duration		Seasonality		Turnover		Conv. rate	TFP	Rev. var.	FTC usage
	mean	st. dev.	share	HHI	worker	contract				
Cl. 1	83.0	38.1	0.72	2,097	2.12	1.61	0.05	4.54	0.23	190.0
Cl. 2	250.4	137.9	0.01	904	1.12	1.13	0.38	6.05	0.23	62.5
Cl. 3	100.3	47.7	0.01	1,077	2.02	1.30	0.27	4.78	0.27	68.7
Total	136.3	69.4	0.08	1,136	1.81	1.29	0.28	5.14	0.26	73.7

Notes. Each row reports the mean of the indicated variable for firms in the corresponding cluster. *Clustering inputs* are variables used in the k-means algorithm (after standardization); *Other characteristics* serve as external validation. Duration is the initial duration of the first FTC in a match, measured in days (mean and standard deviation within firm); seasonality is measured through the share of seasonal contracts and the normalized Herfindahl–Hirschman index of temporary employment days across calendar months ($\times$10,000); worker turnover is the number of workers required to generate 365 employment days; contract turnover is the average number of FTCs per firm–worker match; the conversion rate is the share of matches converted to open-ended positions; TFP is total factor productivity (Wooldridge 2009); revenues variability is the within-firm coefficient of variation of revenues across years; FTC usage is measured as temporary employment days per employee. TFP, revenues variability, and FTC intensity are available only for the subsample matched with CERVED–INPS data.

The variables which do not enter the clustering algorithm provide further support for the mapping between clusters and FTC uses. Cluster 2 stands out for its higher conversion rate (38 percent, versus 5 percent in Cluster 1 and 27 percent in Cluster 3) and higher total factor productivity, consistent with the theoretical prediction that more productive firms screen workers through longer trial periods. Revenue variability is highest in Cluster 3, in line with the buffer-stock hypothesis whereby firms facing greater demand uncertainty rely more heavily on temporary employment to adjust their workforce. Because none of these variables enters the algorithm, the observed patterns constitute independent evidence that the clusters capture economically meaningful differences in firms' motives for using FTCs.

All clustering variables differ significantly across groups. One-way ANOVA tests reject the null hypothesis of equal means for every input at the 0.1 percent level, with F-statistics ranging from about 2,600 for the number of contracts per match to over 200,000 for initial contract duration. A between/within variance decomposition indicates that the seasonal share and contract duration are the most discriminating dimensions, with between-cluster variance accounting for 79 and 53 percent of total variance, respectively.

Figure C15 in the Appendix shows the distribution of Euclidean distances between each firm and the centroid of its assigned cluster, computed from the standardized variables used in the clustering procedure: smaller values indicate firms whose characteristics closely match the cluster's core, while larger values signal greater heterogeneity. Clusters 2 and 3 display tight concentration around their centroids, with mean distances of 1.16 and 1.34, respectively. Cluster 1 is more dispersed (mean distance 2.43), reflecting the fact that seasonal firms can differ substantially in their characteristics, since seasonality is more closely related to sector and geographical location than to individual firms' behavior.

The simple cross-tabulation in Table 3 and the machine-learning classification in Table 4 display highly consistent patterns, with about two thirds of all contracts and firms associated with buffer-stock motives. The higher incidence of seasonality observed at the contract level partly reflects the fact that firms activate multiple FTCs to cover short employment spells, which mechanically increases the share of seasonal contracts relative to firms. Conversely, the lower incidence of contracts signed for screening purposes likely reflects their longer duration and correspondingly lower turnover.

7. Conclusions

This paper describes how Italian firms use temporary work to understand the motivations behind the utilization of FTCs at the firm level. Guided by the theoretical literature, we identify three primary types of temporary employment and map them to the primary reasons firms use FTCs: seasonality, screening, and employment buffer-stocking. Our analysis shows that these three motives can be empirically distinguished. Seasonal use can be identified through administrative flags on individual contracts and the concentration of hiring across months at the firm level. Sector and location explain a substantial amount of its variation. Screening can be predicted through initial contract duration, a characteristic of the first FTCs that firms select when hiring. Firms that consistently offer longer initial contracts have higher conversion rates, even when controlling for workers' characteristics. Unlike seasonality, this variation is largely firm-specific rather than sector- or geography-driven. Buffer-stock use cannot be directly identified in the data. Therefore, we treat it as a residual category and examine how the intensity of FTC use relates to firm characteristics. While seasonal employment is governed by separate factors, screening and buffer-stock use are both linked to firm-level productivity and revenue volatility. More productive firms offer longer contracts and convert more frequently. In contrast, less productive firms facing higher uncertainty primarily use FTCs to adjust employment at the margin. Focusing on systematic users — the 42 percent of firms that use FTCs recurrently and generate nearly 90 percent of temporary employment — and applying a machine-learning classification based on these criteria, we find that seasonal use accounts for about 10 percent of all firms; screening accounts for roughly one-quarter; while buffer-stock use accounts for about two thirds.

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Appendix A. Additional Details

A1. Institutional Background

In Italy, fixed-term contracts (*contratti a tempo determinato*) were introduced in 1962 (Law No. 230/1962). Their use was, however, limited by that law to seasonal work, temporary replacements, or specific short-term projects. In 1997, the so-called *Pacchetto Treu* (Law No. 196/1997) introduced various forms of temporary work, and in 2001 fixed-term employment was substantially liberalized (Legislative Decree No. 368/2001), while the regulation of permanent employment remained unchanged. This reform replaced the earlier restrictive framework with a more general provision, allowing employers to use temporary contracts for any "technical, production, organizational or replacement" reason. The goal was to stimulate employment growth through greater labor market flexibility.[22]

Subsequent measures mainly aimed at reducing the administrative burden of FTCs and regulating their duration. In 2012, the *Fornero Reform* (Law No. 92/2012) sought to narrow the regulatory gap between permanent and fixed-term employment by acting on both sides: it reduced uncertainty regarding dismissal costs for permanent contracts and made it easier to initiate new temporary contracts, while increasing their cost when extended over time. Further changes were introduced by Law No. 78/2014 (the so-called *Poletti Decree*), which eliminated the obligation to justify FTCs and set a maximum duration of 36 months. Finally, the *Dignity Decree* (Law Decree No. 87/2018) partially reversed these provisions, reinstating the requirement to provide an explicit justification for contracts longer than 12 months or for any renewal, and reduced the maximum duration to 24 months.[23]

In parallel, the government also influenced the temporary jobs market through hiring subsidies. Generous three-year social security exemptions were granted in 2015 for new permanent hires and conversions from fixed-term positions, followed by similar but less generous incentives in 2016. In 2017, a new program targeted only firms hiring workers in Southern Italy.

[22] Daruich, Di Addario, and Saggio (2023) analyze the effects of this reform on labor demand.
[23] For an analysis of the impact of the *Dignity Decree*, see Palladino, Sartori, and Grasso (2026).

A2. Clustering Details

This appendix documents the implementation of the firm-level clustering reported in Section 6.2. The algorithm is implemented in Stata (*cluster kmeans*) and partitions the 440,029 systematic users on the basis of the six inputs listed in Table 5, using Euclidean distance.

Inputs and standardization. Because k-means with Euclidean distance is sensitive to the scale of the inputs, each of the six variables is standardized to zero mean and unit variance prior to clustering. We standardize the variables in their original (level) scale rather than applying a prior logarithmic transformation. While several inputs are right-skewed, their levels carry a direct economic interpretation — duration in days, the number of contracts per match, the number of workers required to generate a year of employment — and preserving this scale keeps the resulting centroids interpretable in the units reported in Table 5. The classification is robust in the sense discussed below.

Missing values and variable selection. K-means requires complete cases. The six clustering inputs are non-missing for all 440,029 firms, so the clustering sample coincides with the full set of systematic users. The inputs are not redundant: the largest pairwise correlation, between the firm-level mean of contract duration and its within-firm standard deviation, is 0.55, while all remaining correlations are below 0.48 in absolute value. Each input therefore contributes distinct information on firms' patterns of FTC use, and we retain all six. The two seasonality measures (the share of seasonal contracts and the across-month Herfindahl–Hirschman index) are the most discriminating dimensions across the resulting clusters, accounting respectively for 79 and 53 percent of the total variance of those inputs in a between/within decomposition.

Choice of k and stability. To address the sensitivity of the algorithm to the initial placement of centroids, for each candidate number of clusters k from 2 to 10 we run the algorithm 100 times from independent random starting points. We select the number of clusters that maximizes the average Caliński–Harabasz index, a standard criterion of cluster separation, which attains its highest value at $k = 3$ (Figure C14A). The solution is also stable across initializations: the coefficient of variation of the index across the 100 runs is 0.08 at $k = 3$ (Figure C14). The partition reported in Tables 4 and 5 is the highest-separation solution obtained from 50 further random initializations at $k = 3$.

Appendix B. Additional Tables

TABLE B1. Number of FTCs and Temporary Matches, by Starting Year

Year	Contracts	Firms	Workers	Employment Relationships	
				Number	Share
2013	3,188,245	266,430	1,468,015	1,467,035	19.56
2014	3,377,573	205,811	1,102,469	1,455,343	19.41
2015	3,409,175	181,770	1,093,750	1,464,048	19.52
2016	3,596,666	209,410	1,200,490	1,501,924	20.03
2017	4,429,183	295,602	1,579,535	1,610,661	21.48

Notes. Number of contracts, firms and workers in the full dataset and the number of employment relationships, subdivided by their starting year. Full sample.

TABLE B2. Firm Presence in the Data: N. of Years with at Least 1 FTC

N. of years present	N. of firms	Share of firms	Share of temporary employment days
1	122,977	11.8 %	1.8 %
2	119,716	11.5 %	3.9 %
3	120,018	11.5 %	5.6 %
4	106,063	10.2 %	6.2 %
5	575,679	55.1 %	82.6 %

Notes. Firm presence in the full dataset. In our observation window (2013–2017), firms can be present (have at least one temporary worker) for one to five calendar years. The second and third column report the number and share of firms according to their presence; the fourth column reports the weight of the category of firms in terms of total temporary employment days.

TABLE B3. Sample Composition by Sector and FTC Usage Frequency

		Sporadic		Systematic		Total	
Ateco '07	Sector	N	%	N	%	N	%
B	Mining and quarrying	677	0.1	654	0.2	1,331	0.1
C	Manufacturing	80,342	13.3	87,958	20.0	168,300	16.1
D	Electricity, gas, steam and air conditioning	667	0.1	666	0.2	1,333	0.1
E	Water supply and waste management	2,059	0.3	3,100	0.7	5,159	0.5
F	Construction	114,173	18.9	58,654	13.3	172,827	16.6
G	Wholesale and retail trade	131,176	21.7	74,423	16.9	205,599	19.7
H	Transportation and storage	22,554	3.7	26,999	6.1	49,553	4.7
I	Accommodation and food service	116,494	19.3	101,907	23.2	218,401	20.9
J	Information and communication	13,738	2.3	9,700	2.2	23,438	2.2
K	Financial and insurance	5,855	1.0	3,112	0.7	8,967	0.9
L	Real estate	11,675	1.9	2,975	0.7	14,650	1.4
M	Professional, scientific and technical	28,169	4.7	13,380	3.0	41,549	4.0
N	Administrative and support service	26,131	4.3	25,873	5.9	52,004	5.0
R	Arts, entertainment and recreation	12,442	2.1	12,461	2.8	24,903	2.4
S	Other service activities	38,272	6.3	18,167	4.1	56,439	5.4
	Total	604,424	100.0	440,029	100.0	1,044,453	100.0

Notes. Distribution of firms across sectors (Ateco 1-letter classification) by their use frequency. *Systematic users* meet three criteria over the 2013–2017 period: (*i*) employ temporary workers in at least three distinct years; (*ii*) employ at least two distinct individuals on FTCs; and (*iii*) generate at least 365 employment days in total across all temporary jobs. Firms not meeting these criteria are classified as *Sporadic* users. Percentages are computed within each user type.

TABLE B4. Average Firm Size by User Type

	Sporadic	Systematic
Revenues	1,514.0	8,382.8
Employees	6.5	30.5

Notes. Average firm size by user type over the 2013–2017 period, only for the subset of incorporated firms that can be matched with the CERVED-INPS dataset. Revenues are expressed in thousands of euros. Employees for each year are measured as average across months, before the average across years is calculated. Averages are computed first within each firm across years, then across firms within each user type.

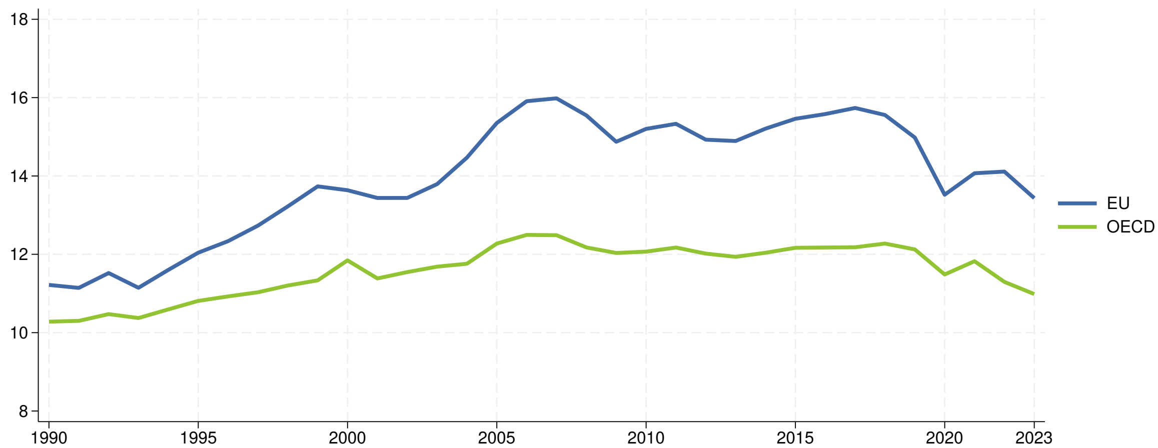
TABLE B5. Regressions: FTC Use Intensity vs. Revenues

	All	Total Factor Productivity			
		min-p25	p25-p50	p50-p75	p75-max
Revenues variability	0.210***	0.150***	0.175***	0.213***	0.249***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
N. of sector F.E.	1,016	798	859	889	896
N.	213,890	51,712	52,892	53,198	52,845
Adjusted R^2	0.235	0.186	0.208	0.241	0.276
Within R^2	–	0.022	0.028	0.038	0.047
$\sqrt{\text{MSE}}$	0.905	0.884	0.869	0.881	0.940

Notes. Results of regressions of (log) FTC use intensity on (log) revenues variability, including six-digits sector fixed-effects. The results are reported for the systematic-users + CERVED sample (for which revenues data are available, see Section 4) in the first column, and then for four sub-groups of firms defined by the quartiles of the total factor productivity distribution. Standard errors are clustered at the sector level and reported in parentheses, and stars indicate standard significance levels: *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$

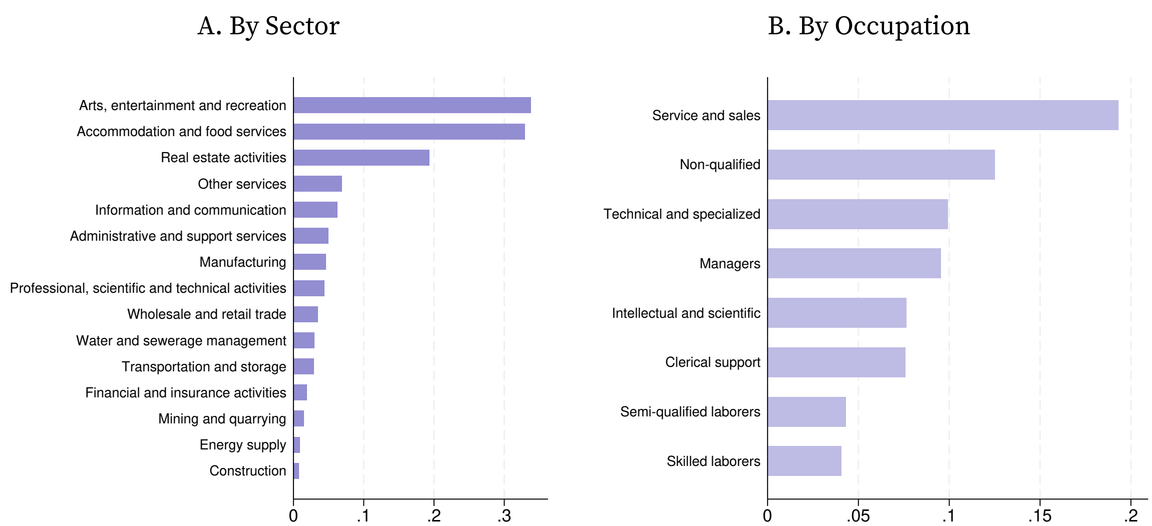
Appendix C. Additional Figures

FIGURE C1. Temporary Employment Share



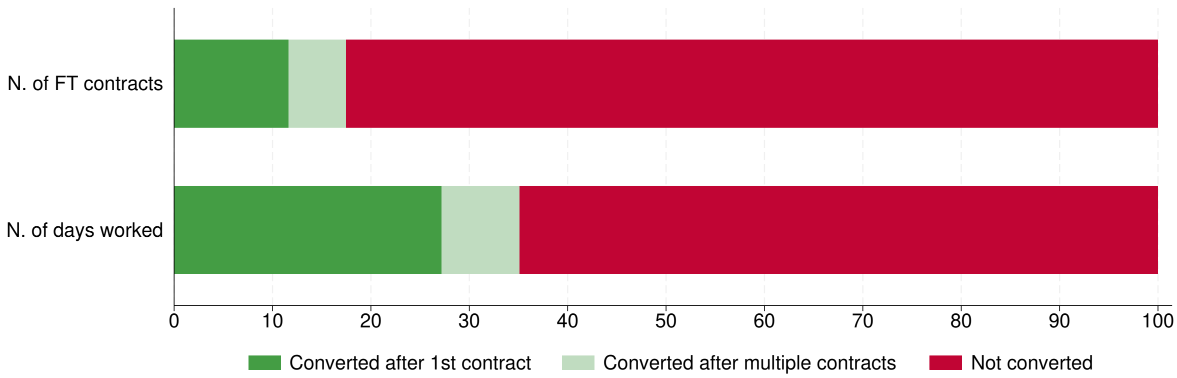
Notes. Share of temporary employment in total dependent employment. Source: OECD – Employment by permanency of the job. See: *Labour force statistics in OECD countries: Sources, Coverage and Definitions* (2023)

FIGURE C2. Share of Employment Relationships Starting with a Seasonal FTC



Notes. Share of seasonal FTCs in total FTCs. Panel A: by macro-sector (Ateco 2007/Nace Rev.2 1-letter classification). Panel B: by occupation (Istat's *Nomenclature and classification of professional units* classification).

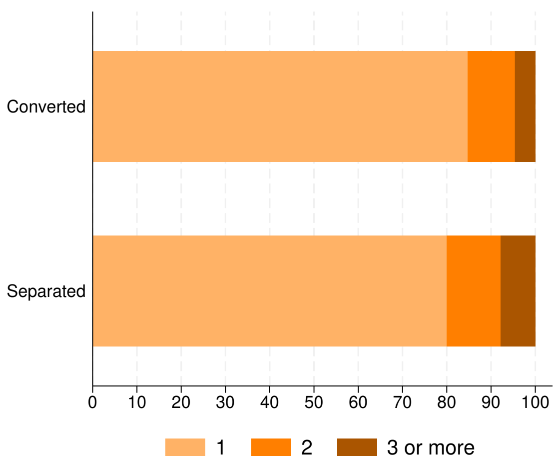
FIGURE C3. Occupational Weight of Temporary Matches, by Conversion Outcome



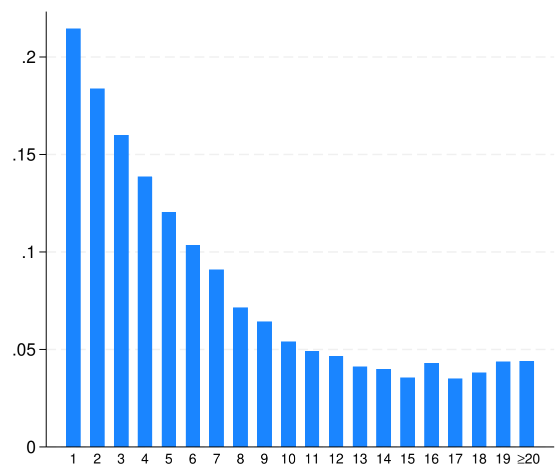
Notes. Distribution of the number of FTCs and of total temporary employment days across the three mutually exclusive outcomes of temporary matches: converted after the first FTC (dark green), converted after multiple FTCs (light green), not converted (red).

FIGURE C4. Number of FTCs in the Employment Relationship and Conversions

A. Share of Employment Relationships by Number of FTCs Used



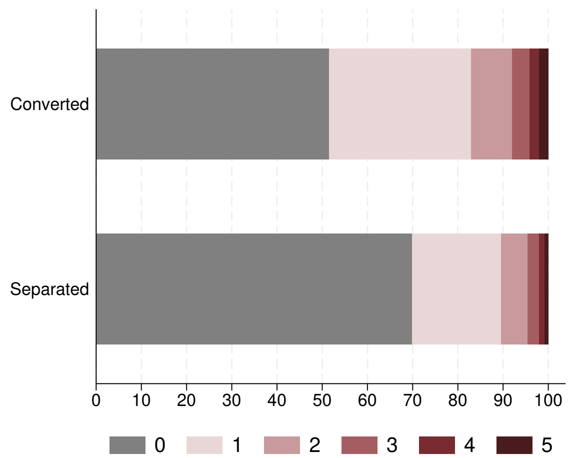
B. Conversion Share by Number of FTCs Used



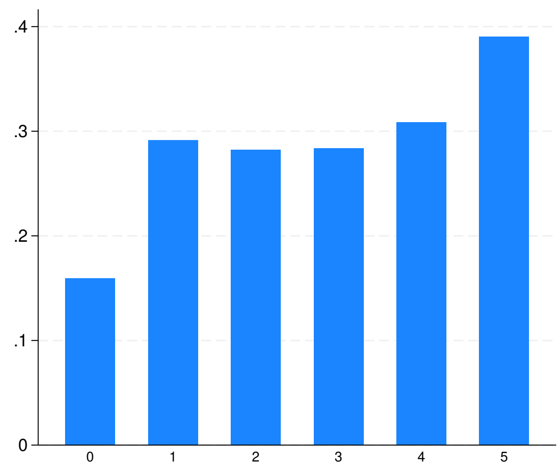
Notes. Panel A: share of employment relationships by number of separate FTCs (spells) in the relationship, reported by conversion outcome. Panel B: share of converted employment relationships, by number of FTCs in the relationship.

FIGURE C5. Number of Extensions to the First FTC and Conversions

A. Share of Employment Relationships by Number of Extensions to the First FTC



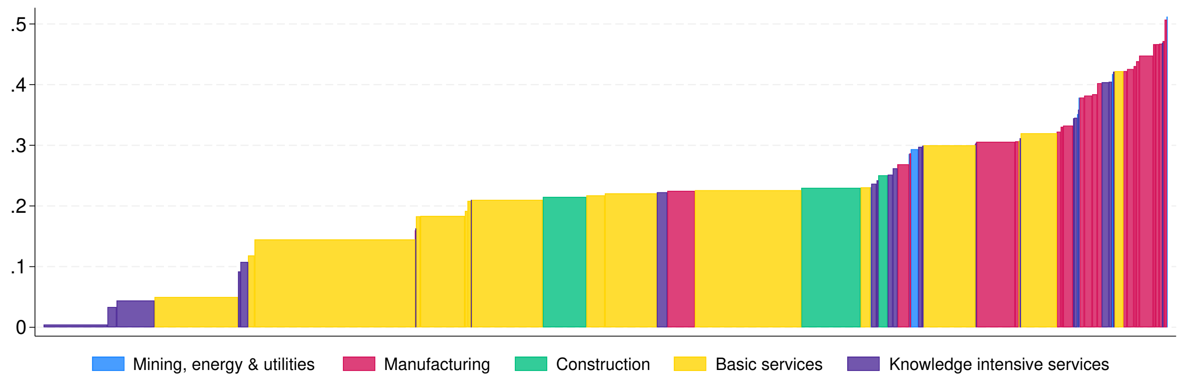
B. Conversion Share by Number of Extensions to the First FTC



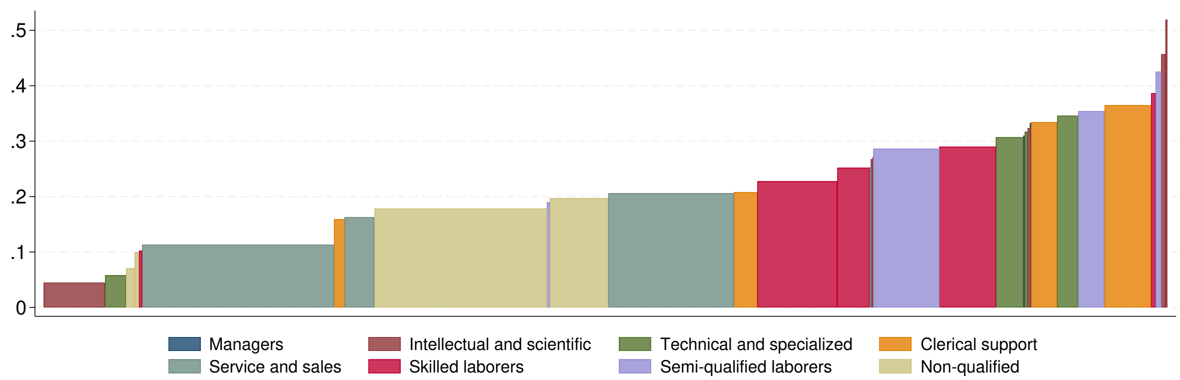
Notes. Panel A: share of temporary employment relationships by number of extensions to the first FTC in the relationship, reported by conversion outcome. Panel B: share of converted temporary employment relationships, by number of extensions to the first FTC in the relationship.

FIGURE C6. Share of Converted Temporary Matches

A. By Sector



B. By Occupation

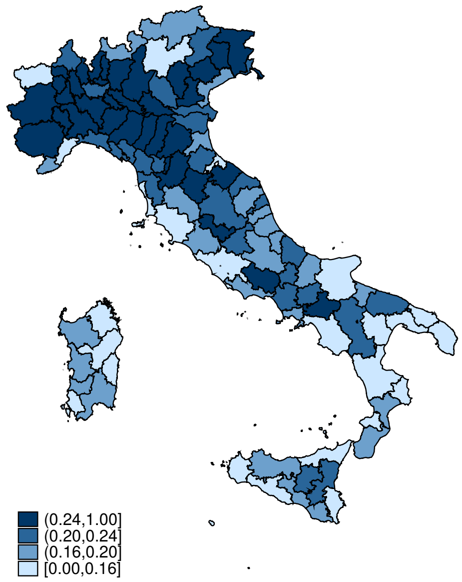


Notes. Share of converted temporary matches by sector (panel A, using 2-digits Ateco 2007/Nace Rev.2 classification) and by occupation (panel B, using Istat's 2-digits *Nomenclature and classification of professional units*). The width of each sector's (occupation's) rectangle is proportional to the number of temporary matches initiated over the period of interest (2013-2017). The colors reflect five macro-sector and eight macro-occupation aggregates; the definition of Knowledge Intensive Services is provided by Eurostat.

FIGURE C7. Share of Converted Temporary Matches, by Province

A. Raw Mean

B. Controlling for Industry Composition

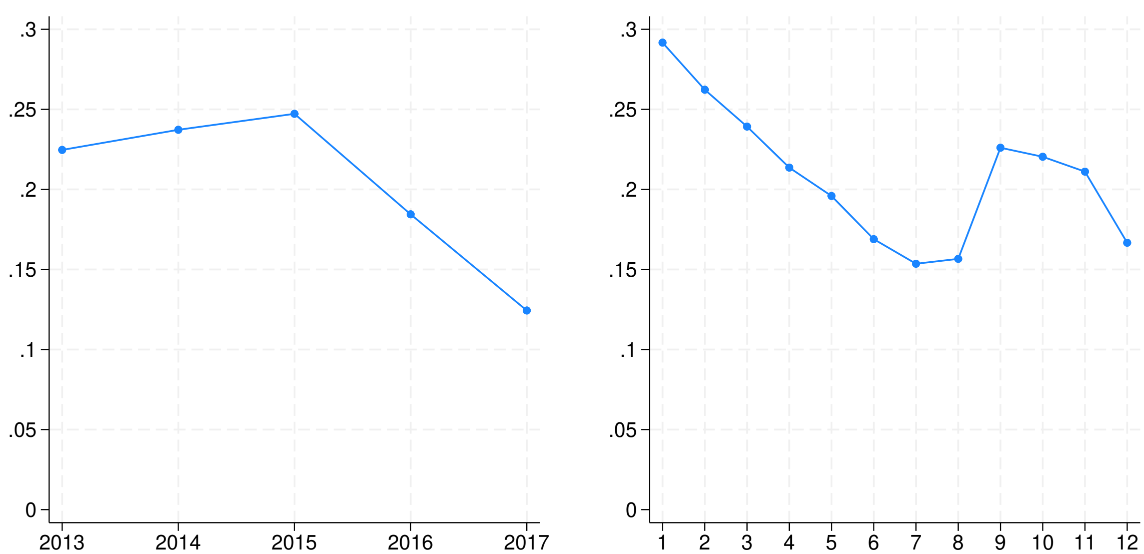


Notes. Share of converted temporary matches across Italian provinces, grouped according to the quartiles of its distribution (2013 – 2017). Panel A: raw mean. Panel B: coefficient on province fixed-effects in a regression including sector (4-digits Ateco/Nace Rev.2 classification), year and calendar-month fixed effects.

FIGURE C8. Share of Converted Temporary Matches

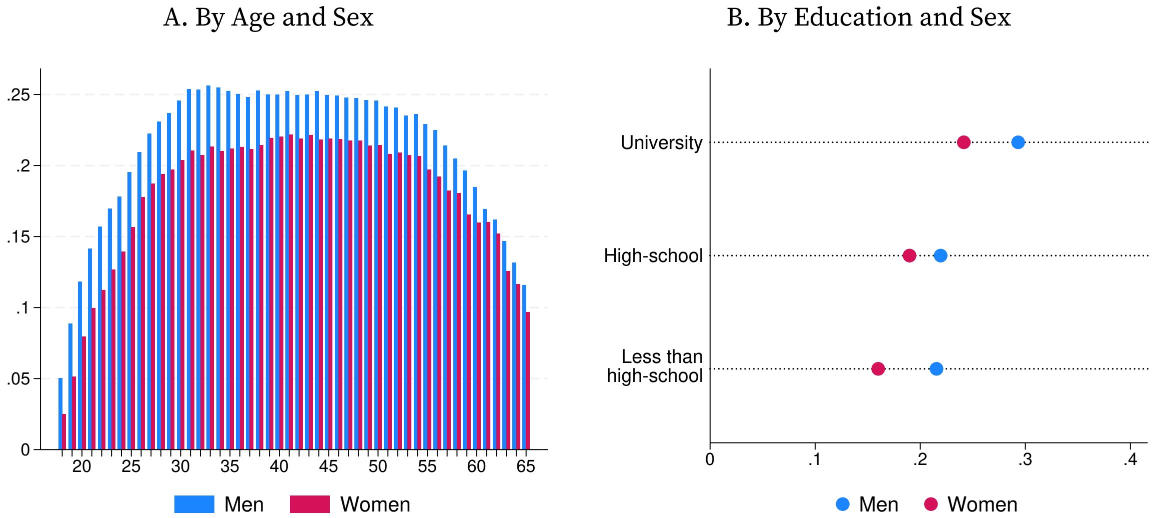
A. By Year

B. By Month



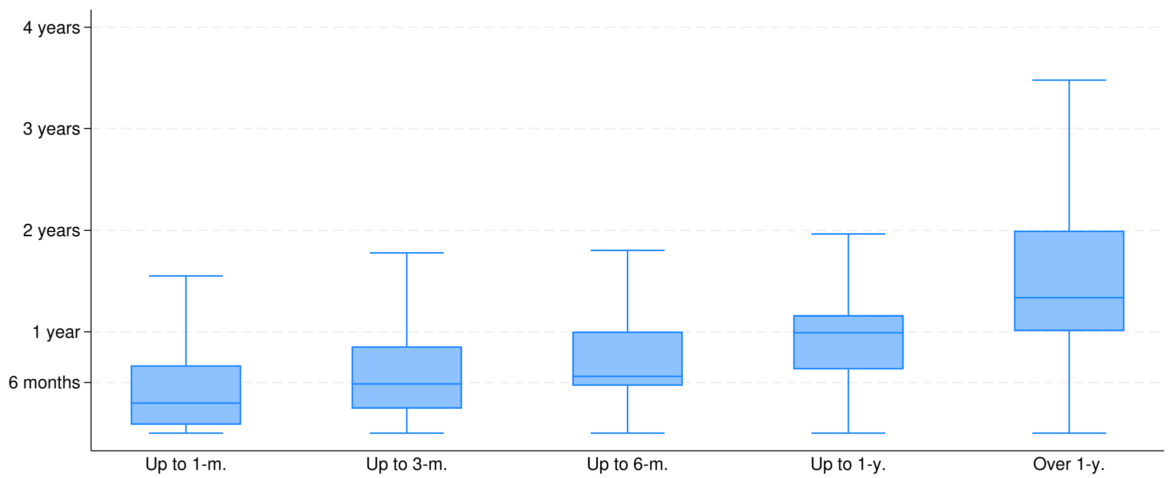
Notes. Share of converted temporary matches by the year and calendar month when the first FTC starts (2013-2017).

FIGURE C9. Share of Converted Temporary Matches



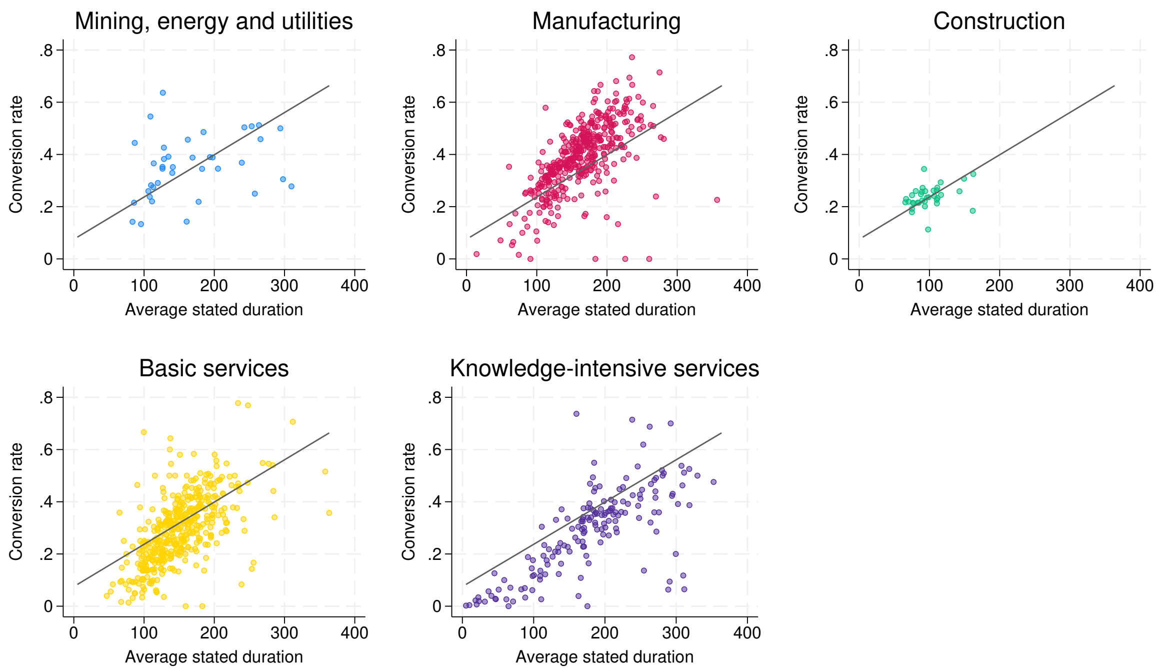
Notes. Share of converted temporary matches across sex groups (2013 – 2017). Panel A: by age at conversion. Panel B: by education level.

FIGURE C10. Total Duration of Temporary Matches, by Duration of the First FTC



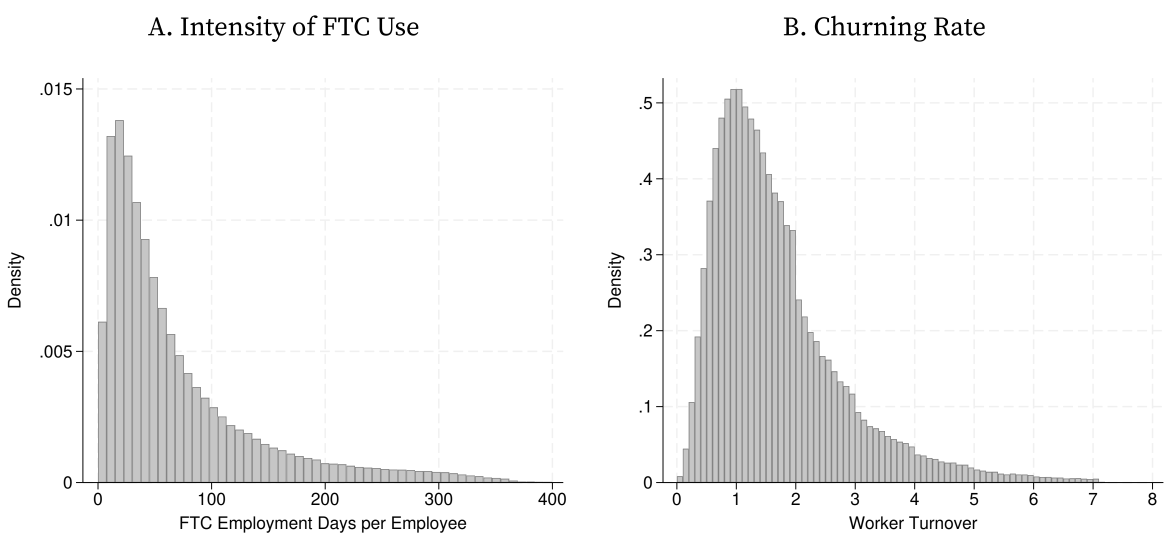
Notes. Distribution of the overall duration of temporary matches (2013 – 2017). This includes the starting FTC, any extension to it and any other recall in the same firm, while post-conversion permanent employment spells are excluded.

FIGURE C11. Temporary Matches Conversion Rate vs. Average FTC Duration



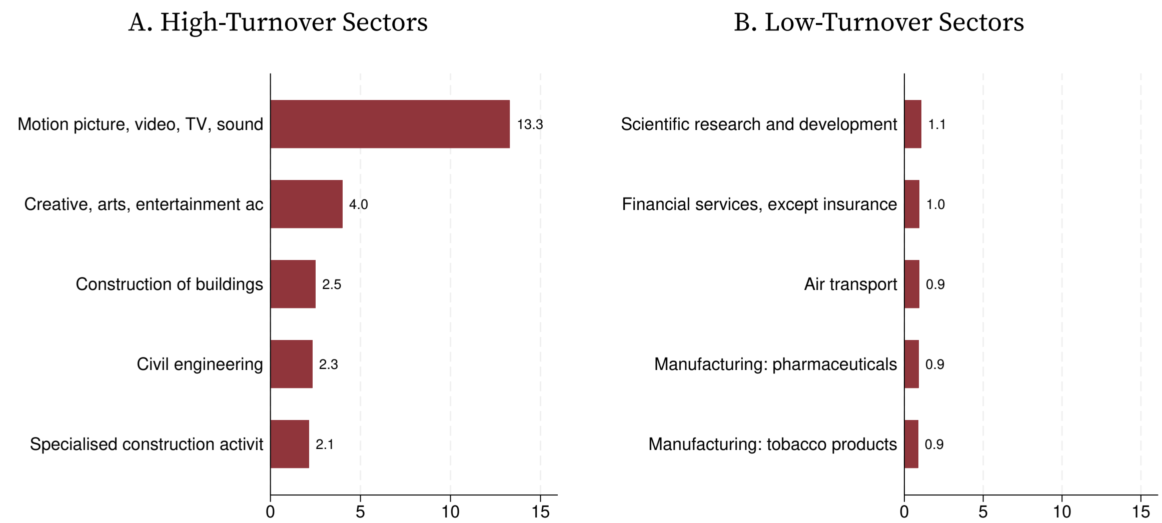
Notes. The graph shows the sector-level share of converted FTCs against the average stated contract duration across the 4-digits sectors belonging to five macro-industries. The line represents the best-fit linear relationship across all sectors.

FIGURE C12. Buffer Stock Use: Main Variables



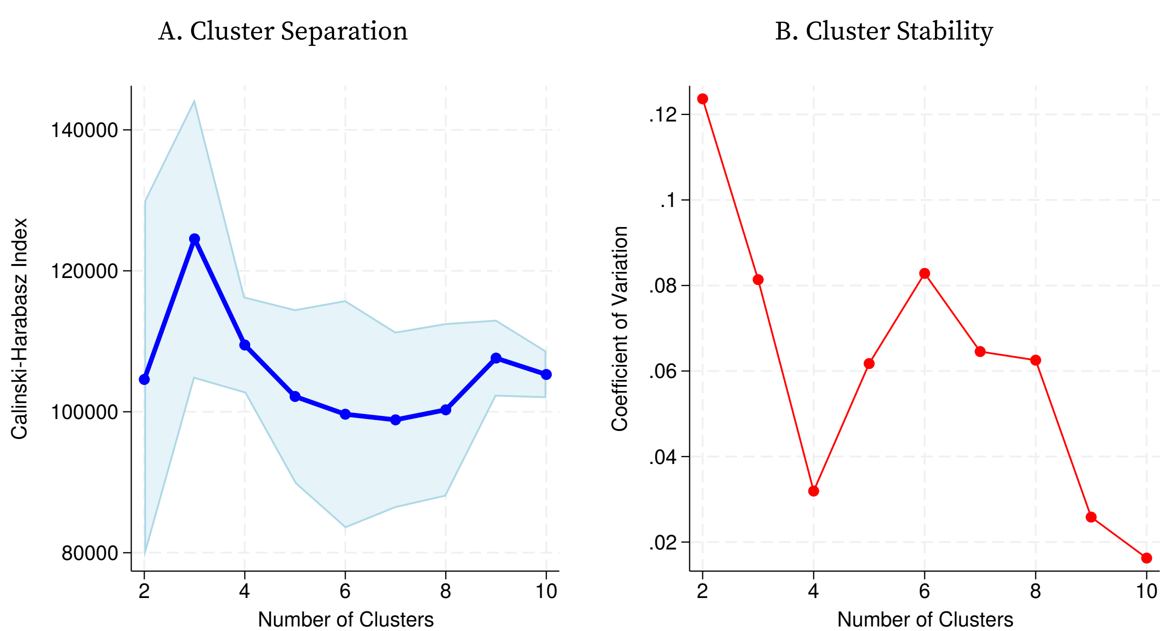
Notes. Panel A: histogram of the firm-specific intensity of use of FTCs. Panel B: histogram of the firm-level churning rate, defined as the number of workers necessary to generate 365 employment days.
Systematic users + CERVED sample.

FIGURE C13. Temporary Worker Turnover



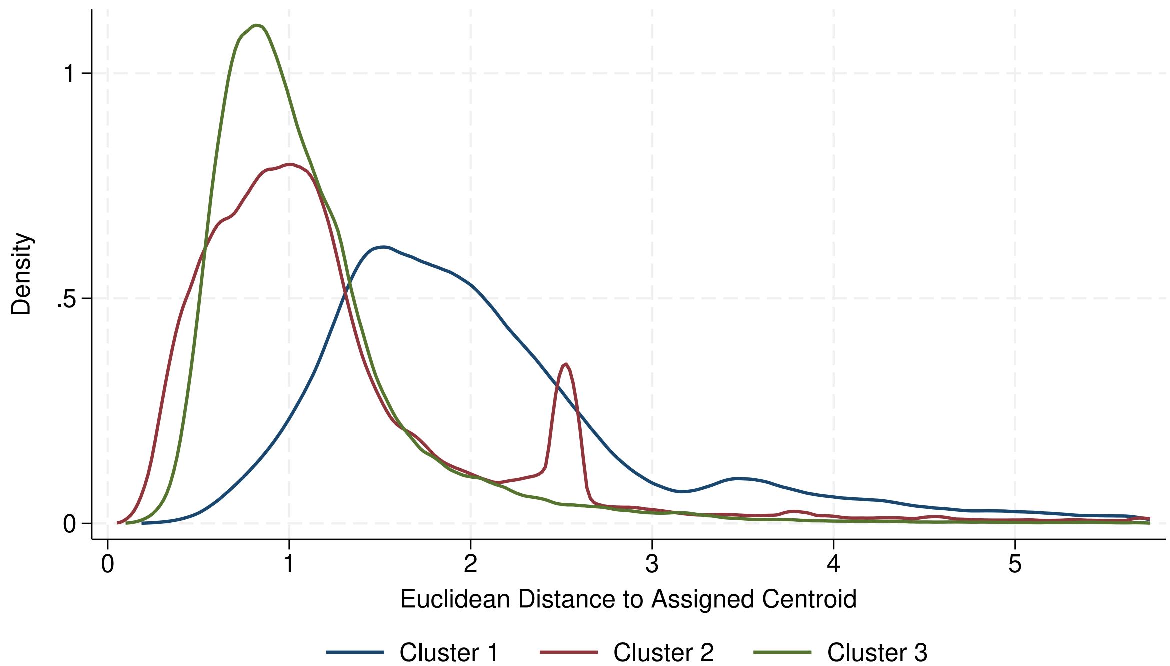
Notes. Average firm-level worker turnover by sector (Ateco 2007/Nace Rev.2 2-digits classification). Worker turnover is defined as the number of temporary workers necessary to generate 365 employment days. Panel A: Top 5 sectors. Panel B: Bottom 5 sectors. Only sectors with at least 10 firms are considered.

FIGURE C14. Optimal Number of Clusters



Notes. Criteria used to choose an optimal number of clusters. For each number of clusters ranging between 2 and 10, we use a k-means clustering algorithm that we run 100 times with different starting values. We then compute the average Calinski-Harabasz Index (Caliński and Harabasz 1974) and its variability across the 100 trials for each number of clusters. In panel A, higher values of the CH-Index indicate better separation between clusters. In panel B, lower values of the coefficient of variation of the CH-Index indicate an increased stability of the index over the 100 estimation rounds.

FIGURE C15. Euclidean Distance of Firms from Their Cluster Centroid.



Notes. The distribution of Euclidean distances between each firm and the centroid of its assigned cluster. Distances are computed from the standardized variables used in the clustering procedure and indicate how far each observation lies from the cluster's core profile *centroid*.