Accepted: 24 September 2024

DOI: 10.1111/ecca.12553

ORIGINAL ARTICLE

Economica LSE

Employer cooperation, productivity and wages: new evidence from inter-firm formal network agreements

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Abstract

Using uniquely rich administrative matched employer–employee data for Italy from 2008 to 2018, we investigate the impact of firms' formal network agreements (FNAs) on firm performance and employee wages. We find an overall significant and economically relevant positive effect of FNAs on various measures of firm performance, but there are no tangible benefits for the workers, and wages decrease slightly, on average. There is, however, marked heterogeneity in the impact on both firms and workers. Estimated rent-sharing equations, as well as other tests that exploit unionization data, suggest that the negative effects on wages can be explained by a decrease in workers' bargaining power following the introduction of FNAs.

KEYWORDS

inter-firm cooperation, formal network agreements, firm performance, total factor productivity (TFP), wages, matched employer–employee data

JEL CLASSIFICATION

L14; D24; J31

1 | INTRODUCTION

Firms, as economic and social actors, are members of numerous networks, which can be formal or informal, structured or unstructured, managed or unmanaged. The primary aim of these interactions is to cooperate to gain advantages, such as sharing information or resources, and engaging in joint activities. The economics and management literature generally agrees that networking creates positive economic returns for cooperating firms, noting that isolation typically leads to poorer performance. Networking among firms can be a significant source of competitive advantage (Dyer and Singh 1998), providing access to relevant knowledge and resources at lower costs (Gulati and Higgins 2003; Zaheer and Bell 2005), and enabling firms to exploit scale economies without the downsides of increased size (Watson 2011). Similarly, recent theoretical contributions on production networks suggest that numerous interactions among firms, often in the form of buyer–supplier relationships, enhance efficiency and firm performance (Bernard *et al.* 2019).

While previous empirical studies agree on the positive effects of inter-firm networking for firms, noting that these effects are stronger for small and medium-sized firms (see Schoonjans *et al.* (2013), or Manello *et al.* (2020) for a recent review), they fail to consider worker-level impacts. As Sachwald (1998) highlights, formal cooperative agreements represent a weaker form of concentration that does not involve an exchange of property rights but may have consequences similar to mergers and acquisitions (M&A), affecting market concentration, firm size and market power. While increased employer size may benefit wages according to the well-known positive relationship between size, productivity and wages (see Berlingieri *et al.* (2018), or Bighelli *et al.* (2023) for a recent discussion), the rising market power from employer cooperation might limit these benefits for workers, as suggested by recent developments in monopsony theory (Manning 2021). Therefore the potential impact of inter-firm cooperation on employees remains unclear theoretically and unexplored at the worker level.

First, networking might lead to increased markups and higher productivity, with expected gains that may be partially shared with employees through higher wages according to rent-sharing mechanisms (Card *et al.* 2014). Second, increasing cooperation facilitates coordination among firms (Krueger and Ashenfelter 2022), leading to a rise in market power akin to market consolidation. This rise in market power is a primary channel for explaining aggregate wage stagnation in recent studies (De Loecker *et al.* 2020; Yeh *et al.* 2022). Moreover, the exchange of information within networks might deter workers from exploring outside options (Sokolova and Sorensen, 2021), reducing their bargaining power, similar to the effects observed in M&A scenarios (Schubert *et al.* 2021). Such frictions to worker mobility across firms enhance monopsonistic power on the employer side, with a negative impact on wages (Manning 2021). The markdown effects on wages can be significant even for small and medium-sized firms, especially if they operate in narrow local labour markets (Naidu and Posner 2022). Finally, Deb *et al.* (2022) find that both markdown and markup effects from rising market power contribute, albeit to varying extents, to wage compression.

In this paper, we provide new evidence and novel insights on inter-firm networking, with a stronger focus on the worker side. We leverage a specific policy instrument, the formal network agreement (FNA), also known as the 'contratto di rete', introduced in Italy in 2009.[1] This instrument allows for precise tracking of firms' involvement in formal cooperation. The FNA typically involves 4–5 members and is used primarily by small and medium-sized firms operating in the same market or at different stages of production/commercialization. We utilize a uniquely rich administrative matched employer–employee dataset provided by the Italian Social Security System (INPS) to investigate the effects of these contracts on both firms and employees. Our analysis covers the entire population of private-sector incorporated firms and their workers over the period 2008–18, encompassing around 2 million firm–year observations, and 8 million worker–year observations. We examine the impact of firm involvement in FNAs from both the firm and worker perspectives, focusing on the productivity-wage pass-through, an aspect that has not been explored before using matched employer–employee data. Our paper addresses two of the four key areas highlighted by Card (2022), where recent empirical literature has advanced the study of imperfect competition in labour markets: (i) the relationship between wages and firm productivity, and (ii) conspiracies and other arrangements to suppress competition.

Regarding the impact on firm performance, we first examine a range of standard indicators (e.g. labour productivity and profitability) and find strong evidence of the positive performance effects of networks, which is compatible with increased markups or markdowns for network members. We then provide novel evidence by considering total factor productivity (TFP), which also confirms these positive effects. To address the non-random decision of a firm to enter FNAs, we use propensity score matching (PSM) techniques combined with a difference-in-differences (DiD) estimator. We conduct robustness checks using both a control function approach and an instrumental variable strategy. In the latter strategy, we use social cohesion at the local community level, interacted with sector-specific probabilities of cooperation, as an instrument for FNA participation. Our firm-level results show that participation in an FNA has a positive and significant impact on TFP, even when accounting for the endogeneity of FNAs in a one-step production function estimation.

The key innovation of our paper lies in examining the impact of FNAs on workers' wages. We estimate multiple-way fixed effects wage regressions, which, in addition to accounting for several time-varying worker and firm characteristics, control for unobserved fixed heterogeneity at the worker, firm and job-match levels. We identify the effect of networking on wages by leveraging individual wage variations through a PSM-DiD model, which compares treated firms and workers with an appropriate control group.

On average, we find that workers do not benefit from their employer's participation in a formal network; instead, they experience a slight wage contraction compared to workers not involved in FNAs. The absence of productivity-wage pass-through contrasts with the positive impact on firm performance, suggesting that firms rarely transfer the benefits gained from FNAs to workers. We also estimate rent-sharing equations, which corroborate this interpretation. Furthermore, we find that the impact on workers is quite heterogeneous and strongly linked to the market power of the firm. Adverse wage effects are concentrated among workers employed in highly productive, medium-sized and less unionized firms, contexts characterized by relatively low worker bargaining power. Consistently, we observe that weaker segments of the labour force, such as workers in low-skill jobs, experience stronger detrimental wage effects.

The remainder of the paper is structured as follows. Section 2 provides a brief review of previous empirical studies on firms' networks. Section 3 describes the main characteristics of the policy instrument 'contratto di rete', and presents our data sources and main variables. Section 4 outlines the empirical framework and identification strategies. Section 5 presents relevant descriptive statistics. Section 6 discusses the results. Finally, Section 7 describes the main implications of this study.

2 | LITERATURE AND BACKGROUND

Predictions of the benefits to the performance of inter-firm cooperation are based on several potential channels suggested by the managerial literature. Networking reduces transaction costs (Lin and Lin 2016), makes resources more accessible and cheaper (Li *et al.* 2015), and facilitates knowledge flows and technological improvements (Vanhaverbeke *et al.* 2009), as well as product or process innovations (Schøtt and Jensen 2016). The extant empirical evidence documents stronger positive effects in small businesses (Schoonjans *et al.* 2013), with weaker impacts for informal and lighter forms of collaborations (Park *et al.* 2010; Watson 2011).[2]

A contribution by Cai and Szeidl (2018) accounts for the endogenous choice of cooperating by running a randomized experiment on Chinese firms, where inter-firm cooperation is defined as the participation of managers in business meetings with other peers, and finds positive effects on sales (+7.8%), profits and labour productivity (+3.7%). Other recent studies on the Italian network contract—the one analysed in this paper—apply DiD estimators or similar techniques on administrative-firm-level data without considering workers. Burlina (2020) finds a positive effect on turnover growth, while Cisi *et al.* (2020) find significant positive effects on value-added and exports, which survive the inclusion of firm-level fixed effects, but provide no evidence on workers. Dickson *et al.* (2021) use a PSM-DiD approach for cross-sectional estimates, and find significant positive effects from networking on employment growth. Fabrizi *et al.* (2022), using a system generalized method of moments estimator, find support for a positive effect on firm size, with stronger effects for environmental-based networks. Finally, Canello and Vitoli (2022) focus on turnover differentials induced by networking for machinery producers inside and outside industrial districts, detecting stronger gains from cooperation within districts. In summary, the existing literature typically relies on standard performance indicators (e.g. survival rates, sales, profits), without focusing on TFP, which is a key element for the expected impact on wages.

Considering the workers' side, the extant literature on how employer cooperation or networking affects job-related outcomes is scant, except for a few studies focusing on firm-level employment (Cai and Szeidl 2018; Dickson *et al.* 2021; Fabrizi *et al.* 2022), without evidence on employees' wages.

In light of the absence of literature on the effect of employer cooperation on wages, we draw insights from recent works investigating the relationship between market consolidation, concentration and wages. Prager and Schmitt (2021) find that market consolidation in the hospital sector in the USA reduces wage growth, mainly for skilled workers, only if M&A are able to induce a considerable effect on market concentration. They use a DiD approach for identifying the causal effect of M&A on wages, and find a slowdown in wages between 1% and 1.5%. Similarly, Arnold (2021) estimates the impact of M&A on wages by comparing M&A workers to a matched control group of workers. He finds that M&A workers' wages remain stable in operations that have negligible impacts on local labour market concentration, while M&A that impact local labour market concentration impose a 2% decline in wages relative to the control sample.

In a similar vein, an increase in employer concentration is expected to lead to reduced wages. Azar *et al.* (2020) compute the Herfindahl–Hirschman index by commuting zone and occupation type in the USA, and document that a relevant share of markets is highly concentrated (around 50%, accounting for more than 15% of total employment). Moreover, they find a negative relationship between labour market concentration and wages. Marinescu *et al.* (2021) use matched employer–employee data from France, and analyse the effect of concentration on new hires, finding that a 10% increase in concentration decreases new hires by around 3%, and wages by 0.5%. Using US data from geographic–occupational labour markets, Azar *et al.* (2022) provide empirical evidence that an increase in labour market concentration is related to a significant drop in average wages. They identify more than 8000 local labour markets that, according to the US merger guidelines, appear highly concentrated, and find a decrease in the average wage by 10% following a passage from the 25th to the 75th percentile of concentration. Market concentration reduces wages also by limiting outside options for workers, as reported by Schubert *et al.* (2021). They use US occupation mobility data and find that an increase in employer concentration from the 75th to the 95th percentile reduces wages by 5%. We argue that a similar mechanism may arise in the case of inter-firm cooperation (e.g. by increasing communication flows among firms), thereby limiting external job-search opportunities for workers.

Our paper is also related to that of Krueger and Ashenfelter (2022), who examine the effects on workers' possibilities and wages of non-poaching clauses, a kind of non-competing agreement among firms. The mechanism on the workers' side is explained by Sokolova and Sorensen (2021). Workers respond to wage cuts by reducing their labour supply or by exploring outside options, which may lead them to leave the firm in pursuit of better external alternatives. The presence of agreements to limit competition among firms, as well as other factors such as geographic isolation or commuting costs, may induce workers to be reluctant to explore outside options, granting employers greater power in setting wages.

Another related strand of recent studies investigates the potential mediating role of unions in curbing the monopsony power arising out of market concentration from employer cooperation. Farber *et al.* (2021) use data on US income and union membership from 1936 to 1986, and find that the density of union membership determines an important part of income inequality. Benmelech *et al.* (2022) focus on US plant-level data over the period 1978–2016, finding a consistent negative relationship between local-level employer concentration and wages, confirmed by using merger activities as an instrument for concentration. Interestingly, they find a stronger negative effect of concentration on wages where the unionization rate is low, shedding light on the potentially relevant mediating effect of unions.

Our paper contributes to this literature by providing a first quantitative analysis of the impact of firms' cooperation on wages, observing formal network formation. Moreover, by estimating specific rent-sharing equations and exploiting indirect evidence on firms' relative bargaining power (e.g. data on union density), we shed light on both rent-sharing and monopsonistic channels in determining the wage effect.

3 | INSTITUTIONAL FRAMEWORK, DATA SOURCES AND VARIABLES

3.1 | Institutional framework: the 'contratto di rete'

In the context of the EU Small Business Act 2008, aimed at sustaining the competitiveness of small and medium-sized enterprises (SME) in Europe, Italian policymakers tried to encourage the aggregation among small firms through a new specific instrument, introduced with Law n.33/2009, the so-called 'contratto di rete'. This new contract, specially designed for small businesses, allows firms to formally cooperate to increase their innovative capacity or market competitiveness on the basis of a shared framework programme. The object of the contract largely fits the standard definition of networks given by Huggins (2001): 'initiatives to bring together firms to co-produce, co-market, co-purchase, or co-operate in product or market development through contractual agreements'. The duration of the agreements is typically five years, but they are often re-confirmed. The required contents of the Italian network contracts include the identification of strategic goals and of the common scope, and the formalization of programmes, activities and investments, as well as the specification of rights and duties for each participant. The normative background is intentionally flexible, but companies should state in detail the programmes and goals of the FNA that they are constituting.[3] The expected benefits are those typical of a larger size (i.e. scale economies, input sharing) reached by small firms that remain formally independent and maintain their organizational flexibility. While network agreements may restrict competition, they are accepted by antitrust authorities for their worthy goals (stimulating technological innovations and improving competitiveness), and since they involve mainly SME, for their alleged limited anti-competitive effects on the whole system.

3.2 | Data sources and matches

Our analysis is based on the combination of three data sources. The first, collected by the Italian Social Security System (INPS), provides yearly administrative matched employer–employee information on the whole population of employees in Italy. It is composed of three parts. The first part is the so-called 'worker archive', which collects personal information pertaining to a worker (e.g. gender, age). The second part is the 'job archive', which contains information on the jobs held by the worker (e.g. job contract type, wage). Finally, there is the 'firm archive', which provides information about the firm, including its location, establishment date, and sector of activity. The second data source, Cerved, is provided by the Cerved Group and collects yearly balance-sheet information, such as value-added, tangible fixed assets and profits, for the population of non-agricultural and non-financial private-sector incorporated companies in Italy. Finally, we retrieve data on inter-firm cooperation from a register provided by InfoCamere, which collects information on all FNAs signed since the introduction of FNAs in Italy (i.e. 2010) until 31 December 2018. It provides information on the name of the FNA, its registration number, the identity of the partner companies involved, and the year of network creation.[4]

The INPS, Cerved and InfoCamere datasets are then matched by using a firm's fiscal number as a firm identifier. We focus on the period 2008–18, that is, starting from two years before the introduction of FNAs to the last year of observation of such agreements. The resulting dataset, which we call 'INPS-Cerved-InfoCamere', covers the population of private-sector incorporated firms in Italy observed from 2008 to 2018, with the exclusion of agricultural and financial companies. For each firm and year, we can identify all of its employees, their job positions, financial variables, and whether or not the firm participates in FNAs. In this paper, we use both the firm-level collapsed dataset and the matched employer–employee (i.e. worker-level) dataset. We use the former to analyse the effect of FNAs on firm performance, and the latter to investigate worker-level effects on wages.

We restrict our attention to incorporated businesses employing at least five employees. First, this serves to clean the data from systematic actions taken to improve the appearance of the company's balance sheet (e.g. showing tangible fixed assets at their acquisition cost, irrespective of their market value). Such practices are more common in very small firms, where accounting procedures are generally less strident (e.g. no statutory audit). Second, this allows meaningful workforce shares to be computed, which we use as controls in our regressions. We concentrate on observations for which we can compute firm performance indicators, including TFP (e.g. available information on value-added, tangible fixed assets, intermediate inputs and gross profit margin, as well as at least two consecutive observations available).[5] We remove firms belonging to the mining industry (a tiny minority) and to sectors in which the level of public intervention is substantial, such as the production and distribution of electricity, gas and water, as well as waste disposal. Finally, for those workers who have multiple jobs in the calendar year, we select the one with the highest wage to be the main job in the year. We then drop jobs with fewer than four paid weeks, and jobs reporting a number of paid days exceeding the theoretical maximum in a year (equal to 312 days).

Our dataset consists of 2,023,088 firm–year observations and around 42 million worker–year observations. For computation reasons, the analysis on the worker–level dataset is carried out on a 20% block random sample, which consists of 8,411,953 worker–year observations.[6] We refer to these firm- and worker-level samples as the 'full samples', as opposed to the PSM samples (see below).

3.3 | Performance indicators

We estimate the impact of FNAs on three firm performance outcomes: (i) TFP, (ii) labour productivity, and (iii) profitability. In this subsection, we describe how each of them is computed.

In order to estimate TFP, we start by considering the production function

$$Y_{it} = f(L_{it}, K_{it}; A_{it}), \tag{1}$$

where the output of firm i in year t (Y_{it}) is modelled as a function of labour (L_{it}) and capital (K_{it}). Here, A_{it} is the TFP of firm i in year t. Such a residual is used as a standard indicator of the overall productivity level of a firm (Van Biesebroeck 2007). We thus retrieve TFP estimates according to

$$A_{it} = f^{-1}(Y_{it}, L_{it}, K_{it}).$$

We assume that the production function in equation (1) is a log-transformed value-added Cobb–Douglas function. A critical issue in the estimation of production functions is the simultaneity of inputs; that is, inputs are endogenous since they respond to a firm's unobserved (by the econometrician) productivity level. In order to solve this issue, we use the control function method developed by Ackerberg *et al.* (2015) (the ACF method), with the extension proposed by Lee *et al.* (2019) (ACF-FE). In a nutshell, Ackerberg *et al.* (2015) propose using a firm's demand for intermediate inputs to proxy for its unobserved productivity. As suggested by Lee *et al.* (2019), we explicitly account for firm fixed effects, thus ensuring that firm-specific persistencies in productivity levels are controlled for (Syverson 2011).

The ACF and ACF-FE methods, together with details on the estimation of equation (1), are discussed in Appendix Subsection A.1.

We then compute labour productivity as the logarithm of value-added over the number of employees.[7] While TFP provides an indicator for the overall productive performance of a company, labour productivity focuses on one critical input of the production process (i.e. labour), and provides general information about the efficiency and quality of human capital in the production process.

Finally, our third indicator of firm performance is profitability. It is computed as the logarithm of the gross profit margin per employee, thereby reflecting a company's ability to produce profits in relation to its size.

3.4 | Worker-level information and wages

Worker-level information includes basic demographic characteristics: gender, age and place of birth. As far as the information on the worker's job is concerned, we have data on the yearly gross earnings, number of days worked over the calendar year, job contract type (i.e. blue-collar worker, white-collar worker, middle manager, top manager or apprentice), contract duration (i.e. fixed-term versus open-ended worker), and working time (i.e. whether the worker has a part-time or full-time contract). Starting from this worker-level information, for each firm and year, we compute the corresponding workforce characteristics, including the shares of workers by gender, age and origin, as well as by job contract type, duration and working time. These variables, which we use as controls in both firm-level and worker-level regressions, accurately describe a firm's workforce composition under various dimensions, and contribute to control for the quality of human capital in the firm.

Our wage measure is a daily wage, computed by dividing a worker's annual earnings by the annual days worked in the same year. As in most administrative data, we do not observe hours of work directly. In general, the hours of work stipulated in a full-time contract contain sector-, firm- and occupation-specific components. We include fixed effects capturing each of these components in our firm- and worker-level regressions. So at least time-invariant heterogeneity in the number of hours of work stipulated by a worker's contract should be adequately controlled for in our regression framework.[8]

3.5 | Participation in FNAs

Thanks to the register provided by InfoCamere, for each firm, we can identify the exact year of entrance into FNAs. Starting from this information, we construct our variables of interest, FNA_{it} and FNA_{jit}. The former, used in firm-level regressions, is a dummy that equals 1 if firm i has ever entered into a network by year t, and 0 otherwise. The latter variable is the same as the former except that it is defined for each worker. Therefore it is a dummy variable that takes the value 1 if a worker j is employed in a firm i that has ever entered into a network by year t. These network variables are both time-variant. We construct FNA_{it} such that once it switches to 1, in the year of entrance into the network, it remains at 1 and does not go back to 0.[9] Technically, after five years since the creation of an FNA, the contract expires automatically, unless it is renewed or transformed. Unfortunately, we do not have this information, and we decide to set the FNA dummy to 1 in all the subsequent years after the creation of the network. We expect that belonging to an FNA implies a structural change in the relationships among the firms involved, and we consequently assume enduring information exchanges and/or coordination after the end of the contract. Furthermore, while the adoption of FNAs started in 2010, their use remained very low in the first years. Considerable increases in the adoption of FNAs started after 2013. Since our observation windows stops in 2018, this potential problem related to the definition of the network dummies is limited to the very few firms that signed FNAs before 2013.[10]

4 | EMPIRICAL FRAMEWORKS

4.1 | Firm-level empirical framework: impact on performance

We model the relationship between FNAs and firm performance according to the equation

$$Performance_{it} = \alpha + \beta_p\ FNA_{it} + \gamma\ X_{it} + \delta\ D_{it} + \eta_i + u_{it}. \tag{2}$$

The dependent variable $Performance_{it}$ indicates the performance of firm i in year t. It is, alternately, TFP, labour productivity and profitability, as defined in Subsection 3.3. The FNA_{it} variable is our variable of interest. Depending on the specification, we insert different workforce- and firm-level controls, included in the X_{it} vector. We include in the D_{it} vector controls for year, size, industry and province fixed effects. Finally, η_i and u_{it} collect residual—fixed and time-varying, respectively—components of performance levels.

A firm's participation in FNAs is likely not random: firms decide whether to participate or not in an FNA as part of a corporate strategy, with potential endogeneity problems regarding the relationship between entering a network contract and unobservable firms characteristics or other managerial aspects. Firms that are typically better performing, or that are experiencing performance boosts, may be endowed with stronger networks of (informal) relationships with their clients and/or suppliers, which may favour the creation of FNAs among them. If this is the case, then one observes higher performance levels associated with firms involved in FNAs, with an overestimation of the true impact if this selection-driven bias is not taken into account. In the same vein, it may also be that firms with typically low performance, or those undergoing a period of financial distress, decide to join an FNA to improve their situation. Again, if this is not controlled for, (downward) biased results are obtained.[11] In sum, there may be a non-random selection of firms into FNAs, which should be duly taken into account.

We first estimate by ordinary least squares (OLS) several versions of equation (2), with increasing sets of control variables. We then pursue fixed effects (FE) estimation. While our FE estimates account for firm-specific time-invariant heterogeneity, as well as a large set of time-varying firm and workforce characteristics, they may still be inconsistent. Unobserved shocks to performance levels as well as other unobserved time-varying factors may influence the decision of a firm to take part in an FNA. We thus conduct a set of additional estimations to address such endogeneity issues. These include: (i) adopting a DiD approach based on the identification of a control group with PSM techniques (we refer to this estimation procedure as 'PSM-DiD'); (ii) adopting the control function (CF) approach suggested by Card and De La Rica (2006); and (iii) instrumental variable (IV) estimation. In the following, we discuss each estimate, and the results are presented in Subsection 6.1.[12]

4.1.1 | PSM-DiD estimation

We first select the firms that participate in an FNA during our observation period. These are the treated firms, and the participation in an FNA is the treatment object of interest. We then use PSM to identify a control group. Such a group includes firms similar to those treated under plenty of observable characteristics, except that they do not participate in an FNA during the entire observation window. Finally, we run an FE estimation of equation (2) on the sample of treated and control firms, which we call the 'PSM sample'. Such an estimation, besides taking into account firm fixed effects, controls for a large set of time-varying firm and workforce characteristics, as well as an array of other fixed effects. By restricting the estimation to the PSM sample, we can assess much more precisely the impact of FNAs on firm performance. This is because a relevant portion of heterogeneity in performance levels and other key characteristics among firms is removed thanks to the PSM procedure, which attenuates any selection-driven bias. In other words, by comparing firms that are very similar to each other, one can consider the treatment—that is, participation in an FNA—to be roughly as good as random. Such a DiD estimation on the PSM sample is adopted as our baseline model and used in most of our firm-level analyses.

In order to define our control group, we follow the recent literature on pre-treatment matching at the firm level (Dickson *et al.* 2021; Comi *et al.* 2020; Maida and Weber 2020), whereby PSM is conducted exclusively on observations before the introduction of the treatment (i.e. the introduction of FNAs by law). Therefore our control group is identified by using observations before 2010 (i.e. 2008 and 2009). The variables used in our PSM procedure include several structural characteristics of the firm and the workforce. In particular, they are: the returns on sales (ROS), expressed as the gross profit margin over revenues; the logarithm of revenues per employee; a vertical integration index, computed as the value-added over revenues; a leverage index, expressed as the net assets over total assets; an index for the rigidity of assets, measured as the ratio between tangible fixed assets and total assets; the capital-to-labour ratio, expressed in logarithms as the ratio between capital and employees; the logarithm of employees; the shares of managers in the workforce (separately for middle and top managers); the shares of female managers over the total number of managers (again, separately for middle and top managers); and finally, fixed effects for industry (three-digit ATECO 2007 classification), size, and province. For each treated firm, we select as control firms the 10 closest (according to the Mahalanobis distance) control firms based on the aforementioned firm- and workforce-level characteristics.[13]

The PSM sample is composed of 219,383 firm–year observations. When considering the matched employer–employee version of this dataset, we have a total of 7,245,911 worker–year observations.

The discussion on the descriptive statistics in Tables 3–5 in Section 5 points out that firms entering FNAs are generally larger, slightly more performing, and more likely to be located in the more economically developed north of the country, as opposed to the average firm of the full sample. The PSM sample is designed to compare treated firms and control firms not entering FNAs that are otherwise observationally similar. This setup implies that the average effect of treatment on the treated (ATT) estimated on the PSM sample might not necessarily capture an average treatment effect (ATE) for the average firm outside that sample. This is a limitation of the analysis that needs to be kept in mind, albeit, as we indicate below (see Table 6 and related discussion), the estimated impacts on the full and PSM samples often do not appear dramatically different in magnitude. At the same time, it is also worthwhile noting that the ATT that we are estimating is a policy-relevant parameter, potentially even more so than the ATE. Indeed, policy-makers who are considering the introduction of fiscal incentives or other measures to expand the participation in FNAs as a mean to promote the aggregation and networking activities of SME need to know the likely impact for precisely the types of firms more susceptible to respond to such measures.

4.1.2 | Control function estimation

We further explore the impact of interest by adopting the method proposed by Card and De La Rica (2006), which, in turn, is based on the results of Imbens (2004). Such a method aims to attenuate the selection-driven bias by directly controlling for the predicted *ex ante* probability of joining an FNA in a standard regression run on the full sample. Essentially, this procedure allows us to control for multi-dimensional firm and workforce heterogeneity, which may influence the decision to join an FNA, in a parsimonious and highly flexible way.

The CF approach requires that a first-stage probit model is estimated for predicting the probability of a firm's participation in an FNA through a rich set of firm and workforce characteristics, by using the observations before the introduction of FNAs (i.e. 2008 and 2009). The first-stage probit model is based on the following regressors: ROS; the logarithm of revenues per employee; the leverage index and the index related to the rigidity of assets, as previously defined; the capital-to-labour ratio; the shares of females, non-native workers, temporary and part-time job contracts, low-experienced workers (i.e. fewer than 15 years of employment), blue- and white-collar workers, apprentices, middle managers and top managers; and the share of female managers over the total number of managers (separately for middle and top managers).

We then run our usual FE regression, augmented with a third-order polynomial in the predicted *ex ante* probabilities recovered from the first step, interacted with year-specific dummies.[14] Adding such controls in the FE regression helps to take into account the potentially higher *ex ante* probability of joining FNAs for certain types of firms.

4.1.3 | IV estimation

To construct an appropriate instrument for FNA, we follow the insight that the propensity of firms to cooperate is influenced by the external environment, as well as by sectoral specificities. Accordingly, our instrument is obtained by interacting (1) a proxy for the probability of the firm to cooperate, given the level of social cohesion characterizing the local environment in which it is immersed, and (2) a proxy measuring the likelihood of networking within the firm's sector and location.

The first part of the instrument (i.e. proxy number 1) is built by focusing on the local environment in which the firm operates, and looks at the level of social cohesion of the local community. When social cohesion is high, the density of social ties, connections, and networks increases. In such contexts, we expect that firms will be more prone to cooperate, also formally, through FNAs. We thus construct, at the municipality–year level, an indicator of social cohesion based on the density of social-purpose organizations over the total number of economic organizations. The former are identified starting from declarations of ATECO sectoral codes and by legal forms.[15] The identified social-purpose organizations include, for instance, mutual entities, consortia, cooperatives, foundations and associations.[16]

The second component for the instrument (i.e. proxy number 2) derives from the observation of sectoral and provincial specificities in the network formation among firms, possibly stemming from structural characteristics of production processes or markets of a given sector. In practice, we construct the proxy by computing the ratio between the number of firms participating in FNAs and the total number of firms in our sample for each three-digit ATECO sector and province, in each year.

Our instrument, constructed as the interaction of these two components, thus varies at the year, municipality and sectoral levels.

4.2 | Worker-level empirical framework: impact on wages

To assess the impact of a firm's participation in FNAs on the workers' wages, we estimate several versions of the following multiple-way FE wage equation:

$$Wage_{jit} = \zeta + \theta_j + \eta_i + \iota_{ji} + \beta_w \ FNA_{jit} + \kappa \ C_{jit} + \nu_{jit}. \tag{3}$$

The dependent variable $Wage_{jit}$ is the logarithm of the daily wage of worker j employed in firm i in year t, as defined in Subsection 3.4. The θ_j variable collects any time-invariant heterogeneities related to the worker. It includes such aspects as the worker's background, for instance, in terms of individual ability or previous work experiences. The η_i variable collects any fixed heterogeneities of the firm in which the worker is employed. It accounts for aspects such as the average performance level of the firm or its 'culture', for instance, in terms of attention to the employees' needs or degree of corporate social responsibility.[17] The ι_{ji} term is a firm–worker match fixed effect that captures time-invariant job-match heterogeneity. Such a match-specific fixed heterogeneity may include the skills and knowledge of worker j that are particularly relevant to firm i. The FNA_{jit} variable is our regressor of interest. As previously specified, it takes value 1 if worker j in year t is employed in a firm i that is part of an FNA. The β_w coefficient is thus our object of interest since it measures the impact of a firm's participation in an FNA on the worker's wage. The C_{ijt} vector collects several worker- and firm-level controls. Depending on the specification, they include such characteristics as the worker's gender, origin, age, job contract type, duration and working time, as well as the corresponding firm-level workforce shares, firm age, and the number of employees in the firm.[18] Depending on the specification, the C_{ijt} vector also includes fixed effects for year, firm size, industry and province. Finally, ν_{jit} is the error term of the regression.

The endogeneity issues to tackle are mainly related to two aspects. The first, discussed in the previous subsection, stems from the non-random selection of firms into FNAs. Unobserved characteristics of the firms, such as the quality of a firm's management, likely influence performance and, consequently, wages. At the same time, they may also influence the probability that a firm joins an FNA. Relatedly, shocks to performance, which might translate into variations in workers' wages, may influence a firm's decision to join an FNA. The second issue is specific to the worker-level analysis and relates to the potentially non-random selection of workers into firms that take part in FNAs. A worker's ability likely influences his wage. At the same time, it may influence the job match. More able workers are likely to be attracted (and selected) into more performing firms, which, in turn, may have a differential probability of joining an FNA. Similarly, performance shocks, besides potentially affecting the decision to take part in an FNA, may entail a reallocation of employer–employee matches within the firm, thereby modifying the ability distribution that the firm can resort to.

These endogeneity issues are tackled in two main ways. First, we control for firm fixed heterogeneity, thereby removing the time-invariant source of selection of firms into FNAs. Second, we perform the estimation of equation (3) on the (worker-level) PSM sample. As discussed before, this sample is restricted to firms that are very similar under plenty of firm and workforce characteristics, so that participation in FNAs comes closer to a random assignment. Endogeneity concerns stemming from the worker's ability are controlled for by introducing worker fixed effects. This also solves the problem related to the potential reallocation of matches. Controlling for worker and firm fixed effects means that we are identifying the effect of FNAs on a worker's wage by using the wage variation that arises from joining an FNA for the *same* worker in the *same* firm, thereby excluding potential reallocation effects stemming from new hires. Moreover, this

TABLE 1 Firms' participation in FNAs—full sample and PSM sample.

Year	Full sample		PSM sample	
	$FNA_{it} = 0$	$FNA_{it} = 1$	$FNA_{it} = 0$	$FNA_{it} = 1$
2008	169,637	0	18,698	0
2009	193,803	0	19,495	0
2010	195,545	33	19,478	18
2011	195,314	322	19,348	162
2012	191,530	864	19,133	451
2013	187,172	1715	18,743	983
2014	184,308	2312	18,447	1448
2015	187,678	2802	18,203	1926
2016	185,863	3284	17,945	2512
2017	165,261	3783	17,544	3440
2018	147,610	4252	17,157	4252
Total	2,003,721	19,367	204,191	15,192

Notes: Firm-level data. The PSM sample is restricted to firms that are observed in 2018.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

within-firm *and* within-worker design effectively removes the match-specific fixed heterogeneity, further reducing omitted variable bias concerns.

In sum, in the most robust specification, we pursue a multiple-way FE regression on the restricted worker-level PSM sample of treated and control firms, which controls for worker, firm and job-match fixed effects, as well as a large set of time-varying worker- and firm-level characteristics.

5 | DESCRIPTIVE STATISTICS

In this section, we report some descriptive statistics, which refer alternately to our firm- and worker-level samples, for both the full and PSM versions.

Table 1 shows, separately for the full and PSM samples, the distribution of firm–year observations by participation in an FNA. As FNAs were introduced in 2010, FNA_{it} is equal to zero for all observations before that year. From 2010 onwards, we detect an increasing participation of firms in FNAs. In 2018, our last year of observation, 4252 out of 151,862 firms in our full sample participated in an FNA (i.e. 2.80%). On average, over the 2010–18 period, FNA_{it} is equal to 1, thus indicating participation in an FNA for 0.96% of the firm–year observations in the full sample. When considering our firm-level PSM sample, the proportion of firms participating in an FNA is higher. Between 2010 and 2018, 6.92% of firm–year observations are part of FNAs, coherently with the 1 : 10 matching ratio adopted (see the discussion in Subsection 4.1). Table 2 replicates Table 1 for the worker-level datasets. When considering the full sample (20% block random sample) over the 2010–18 period, 139,820 worker–year observations out of 8,411,953 observations are employed in firms belonging to FNAs (i.e. 1.66%). When looking at the worker-level PSM, the percentage increases to 7.65%.

Table 3 reports descriptive statistics on the full sample of firms. Consistently with the diffusion of micro and small companies in the Italian industrial structure, on average, they are rather small, with around 18 employees. The median size is even smaller, at around 11 employees. Average revenues are consistently modest, equal to slightly more than 3.3 million euros per year. On average, the firms produce a value-added per employee (i.e. labour productivity) of around

TABLE 2 Workers' participation in FNAs—full sample and PSM sample.

Year	Full sample		PSM sample	
	$FNA_{jit}=0$	$FNA_{jit}=1$	$FNA_{jit}=0$	$FNA_{jit}=1$
2008	721,614	0	581,506	0
2009	793,229	0	601,446	0
2010	795,172	170	608,212	489
2011	792,976	2106	614,542	6114
2012	771,188	5432	612,980	14,503
2013	752,654	10,976	604,361	30,914
2014	745,071	16,255	601,131	51,420
2015	762,589	19,974	612,627	68,455
2016	768,641	23,506	622,263	90,006
2017	707,429	27,965	614,087	125,347
2018	661,570	33,436	618,141	167,367
Total	8,272,133	139,820	6,691,296	554,615

Notes: Worker-level data. The full sample refers to a 20% firm-level block random sample. It thus collects all the employees working in the firms extracted in the 20% random sample from the population of firms. The PSM sample is restricted to workers in firms that are observed in 2018.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

48,000 euros per year. Firms are typically profitable, with an average gross profit margin per employee equal to just above 15,000 euros per year. The average firm age is rather high, at around 14 years, and firms display a relatively low degree of vertical integration, whereby only around 35% of their revenues turn into value-added. Females constitute 35% of the workforce in an average company, and the proportion of non-native workers stands at 14.5%. Prime-age workers, between 30 and 49 years old, make up the great majority of the workers in the average firm (59%). The rest of the workforce is equally split between under-29 workers (20.7%) and over-50 workers (20.3%). The average company is composed of a great majority of blue-collar workers (59%), a substantial proportion of white-collar workers (32.6%), and some apprentices (6.7%). Middle and top managers are residual job categories, amounting to less than 1% and 0.5% of the average firm's workforce, respectively. This is consistent with the diffusion of small firms, in which such job contracts are not common. Finally, 15.3% of the average workforce hold a temporary job contract, and 21.1% work on a part-time basis.

Table 4 reports similar descriptive statistics on the firm-level PSM sample, separately by treatment status, that is, for the treated and control firms. These statistics refer to 2009, the year before the introduction of FNAs. Standardized differences among the two groups of firms are always very small, thereby suggesting that the treated and control firms are indeed very similar. For instance, the average number of employees is around 28 in the control firms and 29 in the treated ones. Similarly, performance indicators, such as ROS, TFP, labour productivity and profitability, as well as the variables related to workforce composition, are very close between the two groups. The treated firms have a higher size than the firms in the full sample (Table 3), in terms of both employees and revenues (around 29 versus 17, and around 4.1 versus 3.1 million euros, respectively, all measured in 2009). Interestingly, these statistics do not show huge differences in the performance indexes of the treated firms versus the full sample before the FNA introduction, which attenuates concerns of selection-driven bias based on performance levels. However, the treated firms typically display slightly higher performance indicators than firms in the full sample, which suggests that a selection, though limited, of more performing firms in FNAs occurs. For instance, labour productivity in the treated firms in 2009 is just below 49,000

TABLE 3 Descriptive statistics of firms—full sample.

Variable	Mean	S.D.	25th percentile	Median	75th percentile
Employees (FTEs)	18.328	25.534	6.596	10.596	19
Employees (log)	2.496	0.812	1.886	2.360	2.944
Revenues (1000 euros)	3313.353	4929.149	735	1527	3569
ROS (gross profit margin over revenues)	0.075	0.110	0.030	0.067	0.118
TFP (log, ACF-FE estimate)	3.890	0.580	3.553	3.886	4.227
Labour productivity (value-added over employees, 1000 euros)	48.223	36.067	29.153	41.174	57.030
Labour productivity (log)	3.705	0.577	3.373	3.718	4.044
Profitability (gross profit margin over employees)	15.088	28.107	3.378	9.182	18.984
Profitability (log)	2.325	1.135	1.689	2.393	3.048
Vertical integration index (value-added over revenues)	0.350	0.189	0.205	0.326	0.463
Firm age (years)	14.168	12.080	4	11	21
Share of female workers	0.350	0.284	0.125	0.286	0.553
Share of non-native workers	0.145	0.196	0	0.077	0.2
Share of under-29 workers	0.207	0.189	0.065	0.167	0.308
Share of workers aged 30–49	0.590	0.186	0.474	0.6	0.714
Share of over-50 workers	0.203	0.169	0.071	0.176	0.308
Share of blue-collar workers	0.595	0.322	0.4	0.667	0.847
Share of white-collar workers	0.326	0.301	0.093	0.226	0.5
Share of middle managers	0.009	0.040	0	0	0
Share of top managers	0.004	0.021	0	0	0
Share of apprentices	0.067	0.118	0	0	0.091
Share of temporary workers	0.153	0.219	0	0.071	0.2
Share of part-time workers	0.211	0.269	0	0.111	0.286

Notes: Observations: 2,023,088. Firm-level data. FTEs stands for full-time equivalents; ROS indicates the returns on sales. All monetary variables are in nominal prices. Profitability (log) is defined for observations with positive values of profitability.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

euros, whereas in the full sample in the same year it is around 47,000 euros. Similarly, an ROS of 8.9% is observed in the treated firms in 2009, while the same feature for the full sample is lower, at 7.2%. Given these differences between the treated firms and the full sample, it is important to concentrate the analysis on the PSM sample, which allows comparing firms that are much more similar, in terms of dimension, performance indexes and workforce composition. Moreover, concentrating on the PSM sample is important given that only a tiny fraction of the firm–year observations in the full sample belong to FNAs (less than 1%, as discussed previously). In other words, focusing on the PSM sample avoids obtaining potentially diluted effects due to the scarcity of treated firms in the full sample.

Finally, Table 5 reports the distribution of observations, for both the firm-level and worker-level full and PSM samples, according to the macro-area and firm size. Coherently with the greater diffusion of firms in northern areas of Italy, more than half of the firm–year observations in the full sample are from the north-west (31.3%) and the north-east (24.3%). The PSM sample presents a more accentuated geographical difference, whereby firm–year observations

TABLE 4 Observable characteristics of firms by treatment status—PSM sample.

Variable	Control firms mean	Treated firms mean	Standardized difference
Employees	28.211	29.280	0.035
Revenues	4552.474	4101.939	0.101
ROS	0.092	0.089	0.027
TFP	3.962	3.968	0.012
Labour productivity	50.945	48.823	0.069
Profitability	17.461	15.981	0.061
Vertical integration index	0.361	0.374	0.070
Firm age	17.693	15.742	0.167
Share of female workers	0.347	0.360	0.050
Share of non-native workers	0.124	0.108	0.110
Share of under-29 workers	0.210	0.223	0.100
Share of workers aged 30–49	0.629	0.625	0.030
Share of over-50 workers	0.164	0.152	0.094
Share of blue-collar workers	0.582	0.537	0.148
Share of white-collar workers	0.340	0.377	0.131
Share of middle managers	0.009	0.010	0.011
Share of top managers	0.005	0.005	0.017
Share of apprentices	0.065	0.072	0.080
Share of temporary workers	0.121	0.150	0.149
Share of part-time workers	0.126	0.159	0.160

Notes: Observations: 19,495. Firm-level data. We report values for 2009, the year before the introduction of FNAs. We report the standardized difference between the control and treated firms (in absolute values).
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

TABLE 5 Descriptive statistics of firms and workers—full sample and PSM sample.

	Full sample		PSM sample	
	Firms	Workers	Firms	Workers
Macro-area				
North-west	31.25%	32.91%	31.71%	32.64%
North-east	24.30%	25.15%	34.54%	33.65%
Centre	21.10%	19.53%	19.65%	19.22%
South and islands	23.35%	22.40%	14.1%	14.49%
Size				
5–9 employees	39.43%	13.43%	13.84%	3.18%
10–19 employees	34.09%	22.76%	34.53%	14.85%
20–49 employees	19.13%	28.71%	35.09%	33.87%
50–249 employees	7.11%	30.78%	16.03%	42.58%
250+ employees	0.24%	4.32%	0.50%	5.53%
Observations	2,023,088	8,411,953	219,383	7,245,911

Notes: The full sample of workers is defined as in Table 2.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

from the northern regions cover around two-thirds of the total observations (31.7% in the north-west, and 34.5% in the north-east). The geographical distribution of worker–year observations in the full and PSM samples follows similar patterns. As regards size, the firm–year observations in the full sample show a clear prevalence of micro and small firms. As much as 39.4% of the total firm–year observations refers to firms with between 5 and 9 employees, a similar fraction (34.1%) refers to companies with 10–19 employees, and a smaller proportion (19.1%) refers to firms with 20–49 employees. In total, 92.7% of the firm–year observations refer to firms with fewer than 50 employees. The pattern is somewhat different in the PSM sample, which, as discussed before, is characterized by relatively bigger companies. In this sample, the proportion of firm–year observations employing fewer than 50 employees decreases to 83.5%, and the most numerous categories are represented by firms with 10–19 employees and 20–49 employees (34.5% and 35.1%, respectively). The worker-level distribution according to firm size follows these patterns: higher proportions of worker–year observations in relatively bigger firms are detected in the PSM sample as compared with the full sample.

Finally, as for worker-level information, the average daily wage of workers is 79.39 euros in the full sample, as compared to 81.46 euros in the PSM sample, using 2009 as the reference year.

6 | RESULTS

6.1 | The impact of FNAs on firm performance

Here, we show the estimation results of equation (2), aimed at exploring the effects of FNAs on the various measures of firm performance described in Subsection 3.3, including TFP, labour productivity and profitability. The estimates are shown in Table 6.[19]

As outlined in Subsection 4.1, for each of the three performance measures, we report different estimation results, starting from simple OLS regressions with basic sets of controls. Specification OLS1 is the simplest specification of equation (2) that we estimate. In this regression, we control for firm size (five classes), industry (defined at the three-digit level of the ATECO 2007 classification), province and year fixed effects. Specification OLS2 adds to specification OLS1 controls for several additional firm- and workforce-level characteristics, including the vertical integration index, firm age, the number of employees (expressed in logarithms), and workers' shares by gender, origin, age, job contract type, job contract duration and job contract working time. Then specification FE adds to specification OLS2 controls for firm fixed effects, thereby delivering within-firm estimates. The standard errors of these estimations, and more generically of all the firm-level estimations in the paper, are clustered at the firm level.

Looking at this first set of estimates (panel A of Table 6), we can see a list full of positive and statistically significant coefficients, which indicates widespread significantly positive associations between a firm's participation in FNAs and its performance outcomes. Across all the performance measures considered, the estimates tend to be larger in magnitude in the most basic OLS specification (i.e. specification OLS1). When inserting richer sets of controls, and particularly those for firm fixed effects, the coefficients somewhat diminish in magnitude, while remaining economically relevant. According to the within-firm estimates, reported in specification FE, a firm's participation in FNAs is associated with significant increases in TFP and labour productivity, as well as in profitability by 2.2%, 2.8% and 5.8%, respectively. Therefore after controlling for firm unobserved time-invariant heterogeneity, as well as a rich set of firm- and workforce-level time-varying characteristics, firms are estimated to experience a significant, economically relevant, increase in their performance, in terms of both productivity and profitability.

As discussed in Subsection 4.1, we pursue (i) PSM-DiD, (ii) CF, and (iii) IV estimations to better account for the non-random involvement of firms in FNAs, due to time-variant unobserved

TABLE 6 Effects of FNAs on firm performance—full sample and PSM sample.

	Dependent variable		
	TFP	Labour productivity (log)	Profitability (log)
	(1)	(2)	(3)
Panel A			
OLS1	+0.059***	+0.072***	+0.129***
	(0.006)	(0.007)	(0.014)
OLS2	+0.028***	+0.042***	+0.071***
	(0.006)	(0.006)	(0.013)
FE	+0.022***	+0.028***	+0.058***
	(0.004)	(0.004)	(0.011)
Observations	2,023,088	2,023,088	1,773,205
Panel B			
PSM-DiD	+0.022***	+0.028***	+0.039***
	(0.006)	(0.006)	(0.014)
Observations	219,383	219,383	204,516
Panel C			
CF	+0.020***	+0.026***	+0.044***
	(0.005)	(0.005)	(0.013)
Observations	1,140,024	1,140,024	1,007,548
Panel D			
IV	+0.038*	+0.092***	+0.197***
	(0.021)	(0.020)	(0.048)
Observations	2,023,088	2,023,088	1,773,205
Panel E			
One-step ACF-FE	+0.013**	—	—
	(0.005)		
Observations	2,023,088		

Notes: Firm-level data. Standard errors (in parentheses) are clustered at the firm level. Specification One-step ACF-FE reports firm-level cluster-robust bootstrapped standard errors. Specification OLS1 controls for size (five classes), industry (three-digit ATECO 2007 classification), province and year fixed effects. Specification OLS2 adds controls for the vertical integration index, firm age, employees (log), workers' shares by gender, origin, age, job contract type, job contract duration and job contract working time. Specification FE adds controls for firm fixed effects. Specification PSM-DiD includes the same controls as specification FE but is restricted to the PSM sample. Specification CF adds to specification FE a third-order polynomial for the *ex ante* probability of participation in FNAs interacted with year dummies. The *ex ante* probability is computed on observations before the introduction of FNAs, in 2010. This estimation is thus restricted to firms observed in 2008 and/or 2009. Specification IV uses the same controls as specification FE, but instruments FNA_{it} with the index of municipality-level social trust interacted with the index of industry- and province-level commitment to cooperation. This IV estimation is based on 2SLS regressions. Specification One-step ACF-FE reports the estimates obtained from the one-step ACF-FE estimation obtained after including FNA_{it}, together with the standard inputs, in the set of endogenous variables.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

factors. Moreover, limited to TFP, we pursue one-step ACF-FE estimation, as discussed in Appendix Subsection A.2. Table 6 also reports these estimation results.

Panel B of Table 6 is related to the PSM-DiD estimation of equation (2), whereby FE estimation (with the same controls as in specification FE) is conducted on the PSM sample. The coefficients are positive, statistically significant, and somewhat near to those of specification FE, when the full sample is considered. According to these PSM-DiD estimates, TFP and labour productivity are estimated to rise by 2.2% and 2.8%, respectively, as a result of joining FNAs, while an increase of 3.9% is estimated to occur for profitability. Figure 1 shows the event study results

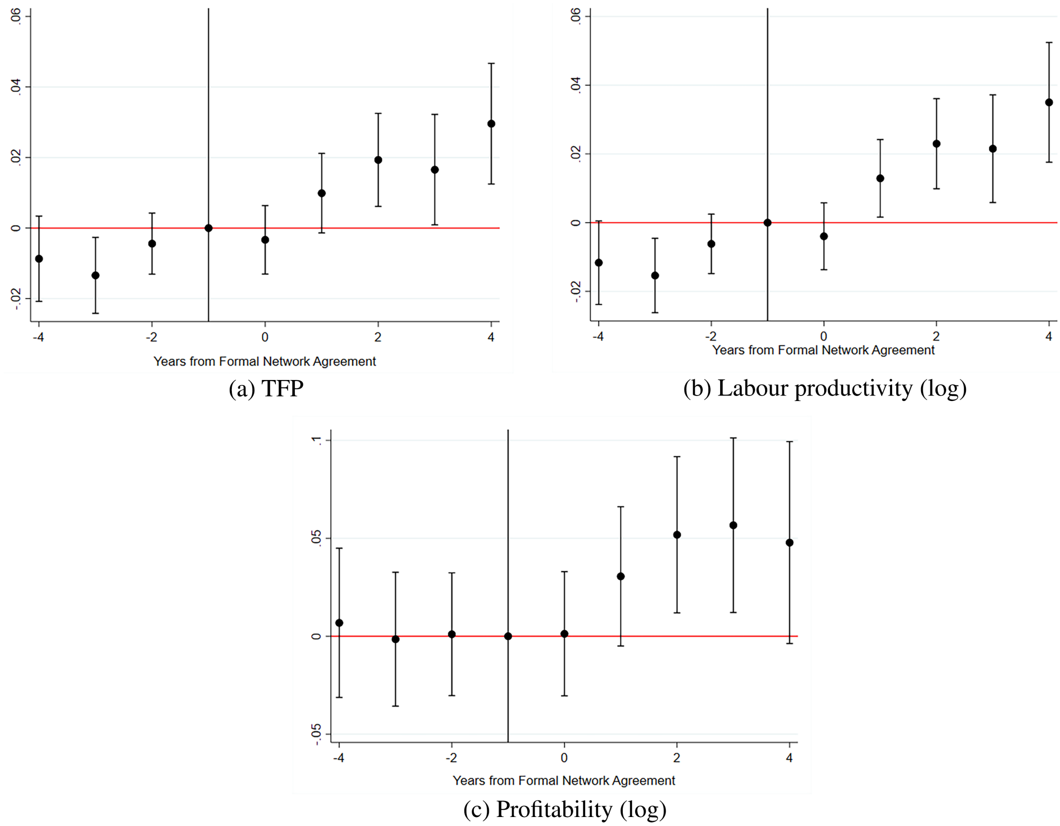

FIGURE 1 Lags and leads estimates of the effects of FNAs on firm performance—PSM sample. *Notes*: The figure plots coefficients for leads and lags up to four years before or following the introduction of an FNA, from a regression based on the specification PSM-DiD. One year before the introduction of the FNA is the omitted category, while the vertical bars represent 95% confidence intervals.

relative to this PSM-DiD specification, for each of the three performance indicators examined. In particular, the FNA_{it} variable is here substituted with lead and lag indicators up to four years before or following the introduction of an FNA in the firm, and the relative estimated coefficients are plotted in the figure (with 95% confidence intervals). We do not detect significant pre-trends in any of the performance indicators, which supports the validity of our PSM-DiD strategy. Moreover, in accordance with the regression results in Table 6, the figure highlights significantly positive, and increasing, effects of a firm's involvement in FNAs on firm performance outcomes over time.

Specification CF, in panel C of Table 6, reports the estimates relative to the CF estimation of equation (2). In short, specification CF adds to specification FE a third-order polynomial for the *ex ante* probability of participation in FNAs interacted with year dummies. Since this estimated probability refers to the year before the introduction of FNAs, this estimation is restricted, starting from the full sample, to firms observed in 2008 and/or 2009. The estimated coefficients are again positive and very similar to those obtained from PSM-DiD estimation.

Panel D of Table 6 reports the estimation results relative to the IV specification. This specification conducts 2SLS estimation of equation (2), instrumenting FNA_{it} with a composite index of social trust (defined at the municipality level) and commitment to cooperation (defined at the industry and province level) and including the same controls as specification FE. Our proposed instrument appears to be a good predictor of a firm's involvement in FNAs, with a first-stage

F-statistic equal to 238.5, above conventional threshold levels. In the second stage, the estimated coefficients associated with a firm's involvement in FNAs are again positive and statistically significant, for all of the considered performance measures. However, the magnitude of these coefficients is somewhat larger compared to the other specifications. While this might reflect the presence of omitted variables negatively correlated with a firm's involvement in FNAs, or better identification of local average treatment effects,[20] it might also be attributable to the lower variability of the instrument than the variable to be instrumented (i.e. a mix of sectoral and geographical levels for the instrument versus the firm level for the FNA_{it} variable). Therefore these IV estimates should be conceived as a further check, pointing to overall positive returns associated with a firm's participation in FNAs.

Finally, panel E of Table 6 shows the results obtained from the one-step ACF-FE estimation of a production function augmented with the FNA_{it} variable, which is treated, like the standard inputs, as an endogenous variable. As previously mentioned, this method can be used only for evaluating the impact on TFP. It represents an alternative to the two-step procedure concerning the TFP impact, where consistent TFP estimates are retrieved in the first step, and in the second step, such indicators are used as the dependent variable. The estimated impact is again positive and statistically significant, equal to 1.3%, thus slightly lower in magnitude as compared, for instance, to PSM-DiD estimates (i.e. 2.2%).

All in all, we find widespread positive returns associated with a firm's participation in FNAs, which translate into increased productivity—both TFP and labour productivity—and enhanced profitability levels. Our results confirm most of the previous findings in the literature (Manello *et al.* 2020; Burlina 2020; Fabrizi *et al.* 2022), using a new and fine-grained matched employer–employee database allowing not only richer controls at the firm and worker levels but, most importantly, to extend those findings to TFP. Interestingly, the detected TFP premia from formal cooperation remain consistent, even if reduced in magnitude, after the inclusion of networking among the endogenous variables in the one-step approach.[21]

In supplementary analyses, we detail some relevant dimensions of heterogeneity in the estimated effect (see Appendix Subsection A.3). We find significant differences in the impacts, with the network contract aligning well with the original policy goal. Specifically, we observe stronger performance gains for smaller firms, located in more disadvantaged areas, and with lower productive performance.

6.2 | The impact of FNAs on wages

A crucial question arises at this point: do the positive performance impacts of a firm's involvement in FNAs translate into higher wages for the workers? Answering this question is the object of the present subsection. Here, we discuss the results obtained from the estimation of various versions of equation (3). The results are reported in Table 7.[22]

As mentioned in Subsection 4.2, we start from basic specifications of the equation, then progressively add controls. In total, we perform the estimation of seven different specifications, one in each row of Table 7. Moreover, each regression is conducted on both the full sample (this is derived from a 20% block random sample) and the PSM sample of workers. The first specification reports the raw wage differential between workers in firms participating in FNAs and workers in firms that are not part of FNAs, thereby inserting no controls in equation (3). Specification OLS1 adds controls for the worker's gender, origin and age (expressed as a cubic polynomial), as well as province and year fixed effects. In addition, specification OLS2 controls for the worker's job contract type, duration and working time. Specification OLS3 further adds firm-level controls, which include firm age, the number of employees (in logarithms), and workforce shares by gender, origin, age, job contract type, job contract duration and job contract working time. Moreover, it accounts for size (five classes) and industry (three-digit ATECO 2007 classification) fixed effects.

TABLE 7 Effects of FNAs on wages—full sample and PSM sample.

	Full sample	PSM sample
Raw	+3.56%***	−1.12%***
	(0.002)	(0.001)
OLS1	−0.18%	−3.93%***
	(0.002)	(0.001)
OLS2	−1.15%***	−3.52%***
	(0.001)	(0.001)
OLS3	−0.77%***	−2.36%***
	(0.001)	(0.001)
Firm FE	−0.01%	−0.21%***
	(0.001)	(0.001)
Worker FE	−0.37%***	−0.50%***
	(0.001)	(0.001)
Job-match FE	−0.47%***	−0.32%***
	(0.001)	(0.001)
Observations	8,411,953	7,245,911

Notes: Dependent variable: $Wage_{jit}$. Worker-level data. Standard errors (in parentheses) are clustered at the worker level. Specification Raw has no control variables. Specification OLS1 controls for gender, origin, a cubic polynomial in age, and province and year fixed effects. Specification OLS2 adds controls for the job contract type, duration and working time. Specification OLS3 adds firm-level controls, which include firm age, employees (log), workers' shares by gender, origin, age, job contract type, job contract duration and job contract working time, and size (five classes) and industry (three-digit ATECO 2007 classification) fixed effects. Specification Firm FE adds to specification OLS3 controls for firm fixed effects. Specification Worker FE adds to specification OLS3 controls for worker fixed effects. Specification Job-match FE adds to specification OLS3 firm and worker fixed effects (i.e. job-match fixed effects). The full sample is defined as in Table 2.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

The fourth row of the table refers to specification Firm FE, which, in addition to specification OLS3, includes firm fixed effects. The subsequent specification (Worker FE), instead, does not include firm fixed effects, but controls for worker unobserved fixed heterogeneity (i.e. it includes worker fixed effects). Finally, specification Job-match FE, in the last row, adds to specification OLS3 both firm and worker fixed effects, thereby controlling for firm, worker and job-match unobserved fixed heterogeneity, as well as a large set of time-varying worker- and firm-level characteristics.

Considering the full sample, we can see that the raw wage gap between workers employed in firms involved in FNAs and those who are not is positive in favour of the former, equal to +3.56%. However, we know that many observable and unobservable factors might confound this raw estimate. When pursuing simple OLS estimation with progressive sets of controls, at both the worker and firm levels, we can see that the gap changes its sign, becoming negative (specifications from OLS1 to OLS3) and significant (specifications OLS2 and OLS3). In particular, according to specification OLS3, the wage differential between the two categories of workers is equal to −0.77%, meaning that the workers employed in firms with active FNAs are paid, on average, 0.77% less than workers employed in firms without participation in FNAs, after controlling for a variety of worker- and firm-level observable characteristics. Further accounting for unobserved heterogeneity, at either the firm level (specification Firm FE) or worker level (specification Worker FE), or both (specification Job-match FE), does not alter the finding of a non-positive effect of FNAs on wages. According to the most robust specification, Job-match FE, in which we exploit the within-firm *and* within-worker variation only to identify the coefficient of interest, a negative and significant wage gap associated with FNAs, equal to −0.47%, is detected.

The same conclusion is reached if we restrict attention to the PSM sample. In this case, thanks to the PSM procedure, we compare firms that are similar under numerous observable characteristics, as explained in Section 4. Because of this, negative coefficients emerge, starting from the simplest regressions, even in the first specification (raw wage gap equal to −1.12%). Progressively adding controls, specifically those for unobserved firm and/or worker heterogeneity (specifications from Firm FE to Job-match FE), confirms the negative wage gap to the detriment of employees of firms taking part in FNAs. The point estimate obtained from the most robust specification (Job-match FE) applied to the PSM sample is −0.32%. This means that the wages of workers experiencing their firms' involvement in FNAs increase by 0.32% less than the wages of workers whose firms do not enter FNAs, thus suggesting a negative impact of FNAs on wages.

While smaller in magnitude, such negative effects on wages are coherent with the recent observational evidence on M&A and market concentration. Prager and Schmitt (2021) report a slowdown in wages between 1% and 1.5% for skilled workers from hospital mergers; Arnold (2021) detects a contraction of 2% for relevant M&A in the USA; Marinescu *et al.* (2021) find a decrease of around 0.5% for new hires linked to concentration increases in France.

In sum, regarding our initial inquiry about whether the observed overall positive performance impacts translate into higher wages for the workers, it seems that the answer is a negative one. While the predicted impacts on firms are overall positive and economically relevant, no benefits—on the contrary, slight detriments—are observed on the worker side.[23]

In Appendix Subsection A.4, we explore a set of moderating analyses on the impact of FNAs on workers' wages. Our results indicate that the wage effects vary significantly by firm type, aligning with the primary objectives of the policy instrument and theoretical predictions. Contrary to the overall effect, we observe modest positive impacts on wages for small firms, which are less productive, and situated in less developed areas. In these contexts, where performance advantages are more pronounced, we detect a partial transfer of benefits to workers. Conversely, negative wage effects are evident in more competitive firms with greater bargaining power—specifically, larger firms, located in wealthier areas, and highly productive. In these cases, the benefits accrued by employers are not shared with employees, resulting in reduced wages.

In the next subsection, we explore whether lowered bargaining power of workers as a result of FNAs might be an explanation behind this finding. In Subsection 6.4, we then provide more evidence on such a mechanism through the estimation of rent-sharing equations.

6.3 | The role of workers' bargaining power

If the monopsonistic mechanism is in place, then we should detect more pronounced negative effects on workers in environments where their bargaining power is lower. In such scenarios, the likelihood of FNAs serving as tools for monopsonistic behaviour by firms rises, enabling firms to retain the advantages of FNAs without passing them on to workers in the form of increased wages. To examine this mechanism, Table 8 investigates the presence of heterogeneities in the wage impact based on the relative bargaining power of workers. We utilize two proxies to measure this aspect. The first proxy exploits data on unionization. Previous studies by Farber *et al.* (2021) and Benmelech *et al.* (2022) indeed suggest that a significant deterrent to employers' power is the presence of unions and the density of their membership. The second proxy, on the other hand, is based on relative average wages.

As concerns the first proxy, we utilize data from the 2010 RIL survey ('Rilevazione Longitudinale su Imprese e Lavoro'), conducted by the National Institute for Public Policy Analysis (INAPP). The RIL is a comprehensive firm-level survey that covers a representative sample of Italian companies and includes information on each firm's unionization levels. Specifically, it provides the percentage of employees within each firm who are members of trade unions. Leveraging this information, we calculate the average unionization rate at the industry level (based on

TABLE 8 Workers' bargaining power and FNAs—PSM sample.

			Observations
Unionization rate			
High	−0.23%***	(0.001)	3,268,467
Low	−0.36%***	(0.001)	3,977,444
Relative average wage			
High	−0.06%	(0.001)	2,832,961
Low	−0.42%***	(0.001)	4,183,529

Notes: Dependent variable: $Wage_{jit}$. Worker-level data. Standard errors (in parentheses) are clustered at the worker level. The unionization rate is defined at the industry level (two-digit ATECO 2007 classification) and refers to 2010. This information is retrieved from RIL-INAPP data. It is computed as the industry-level average share of workers belonging to a union over the total number of workers. We then classify a firm (and thus their workers) as highly unionized if it operates in an industry characterized by an above-average unionization rate, whereas the opposite applies for firms with low unionization rate. The relative average wage is defined starting from the year-specific average wage at the level of province, sectoral collective contract (CCNL) and job contract type, and by comparing the latter to the same feature defined at the firm level. In the case where this firm-level average wage is above that at the province level, workers are classified in the 'high relative average wage' category, whereas the opposite holds for the 'low relative average wage' category. All the estimations are based on specification Job-match FE of Table 7.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

the two-digit ATECO 2007 classification). Subsequently, we categorize the firms in our sample based on their industry-level unionization rates as obtained by the RIL survey. Firms operating in industries with above-average unionization rates are classified as highly unionized, while those in industries with below-average rates are considered low unionized. We then conduct our wage equation estimations separately on the resulting worker-level split samples, that is, on the sample of workers in highly unionized firms and the sample of workers in low unionized firms.[24]

Regarding the second proxy, which is based on relative average wages, our approach is as follows. First, we compute average wages specific to each year, province, sectoral collective contract (known as 'contratto collettivo nazionale del lavoro', CCNL) and job contract type (e.g. blue-collar workers, white-collar workers, middle managers). This entails calculating the average wage for each CCNL and job contract type within each province for every year. Then we compare these province-level average wages with the corresponding features defined at the firm level. This involves generating, for each year and firm, the average wage for each CCNL and job contract type.[25] If a firm's average wages for specific CCNLs and job contract types exceed the province-level averages, then we classify its workers into the 'high relative wage' category. Conversely, if a firm's average wages fall below province-level averages, then its workers are classified as belonging to the 'low relative wage' category. After identifying these two classes of workers, we conduct the standard estimations separately on each category. We interpret the former category, consisting of workers with relatively high wages, as indicative of higher bargaining power, while the latter class suggests lower bargaining power.

Examining Table 8, we observe that the impact of FNAs is more negative for workers in low unionized firms and for those with relatively low wages. Regarding unionization, the effect on workers' wages in low unionized firms is estimated to be −0.36%, which is approximately 56% higher in absolute terms than the estimated impact on workers in highly unionized companies (−0.23%). This result aligns with the findings of Benmelech *et al.* (2022), which highlight higher wage slowdowns in contexts characterized by lower unionization rates. The disparity becomes more pronounced when considering the relative average wage, our second proxy for workers' bargaining power. Workers with relatively high wages are estimated to experience no substantial effect on their wages following their firm's involvement in FNAs. Conversely, workers with relatively low wages encounter a significant negative effect amounting to −0.42%.

Taken together, these results suggest that the negative effects of FNAs on wages manifest themselves in contexts where workers' relative bargaining power is lower, that is, where the increasing market power effect of FNAs can be consistently bigger.

6.4 | Evidence from rent-sharing equations

The final piece of evidence supporting the observed trend, wherein firms experience positive performance effects that often fail to translate to their workers, is derived from rent-sharing equations. In practical terms, we estimate the regression

$$\begin{aligned} Wage_{jit} &= \zeta + \theta_j + \eta_i + \iota_{ji} + \beta_{w1}\ FNA_{jit} + \beta_{w2}\ \hat{\xi}_{jit} \\ &\quad + \beta_{w3}\ FNA_{jit} \times \hat{\xi}_{jit} + \kappa\ C_{jit} + \nu_{jit}, \end{aligned}$$

where all the variables are the same as in equation (3), except that we expand the set of regressors with (i) $\hat{\xi}_{jit}$ and (ii) the interaction between such a variable and FNA_{jit}. The $\hat{\xi}_{jit}$ variable is the (estimate of the) innovation in the firm i productivity level in year t, which we obtain from our ACF-FE estimation of TFP.[26] Notably, $\hat{\xi}_{jit}$ is defined at the firm and year level. We nonetheless add the j subscript to indicate that this equation is at the worker level. In practice, $\hat{\xi}_{jit}$ is a measure of the productivity shock experienced by firm i—in which worker j is employed—in year t. Importantly, as discussed in Appendix Subsection A.1 (equation (A9)), such a productivity shock is unexpected and unpredictable by the firm. This serves to avoid potential endogeneity issues typically linked with the non-random productivity in rent-sharing equations (Card *et al.* 2014). The β_{w2} coefficient thus captures the elasticity of wages to the firm's productivity shocks. We expect it to be positive, so that when the firm undergoes periods of booms, they translate, at least to some extent, into higher wages for the workers. The more recent overview provided by Card *et al.* (2018) finds that the typical rent-sharing elasticities are between 5% and 15%, even if more recent studies report heterogeneous and out-of-scale values for specific subgroups of workers (Allan and Maré 2022). Then we add the interaction between FNA_{jit} and $\hat{\xi}_{jit}$. The related coefficient, β_{w3}, is the main object of interest. This coefficient sheds light on the rent-sharing effect linked directly to the firm's participation in FNAs. Essentially, it quantifies the extent to which the productivity gains associated with FNAs are distributed to workers in the form of increased wages. Finally, β_{w1}, the coefficient associated with FNA_{jit}, quantifies the direct effect of FNAs on workers' wages (i.e. what we estimated in Table 7).

As usual, our rent-sharing estimations are based on specification Job-match FE, thereby accounting for worker, firm and job-match fixed effects, together with the usual set of time-varying worker- and firm-level controls. We estimate such a rent-sharing equation on the PSM sample of workers, as before. We first consider the overall PSM sample, and then run the estimations on the split samples based on the categories in Table 8, that is, by unionization rate and relative average wage. The results of these estimations are reported in Table 9.

Looking at column (1) of Table 9, concerning the overall sample, we can see that the estimated β_{w1} is negative, significant, and equal to −0.34%, virtually the same point estimate found in the worker-level estimation without the rent-sharing effect (i.e. −0.32%, last row and column of Table 7). This thus confirms the overall negative effect of FNAs on workers' wages. The estimated β_{w2} coefficient, associated with the $\hat{\xi}_{jit}$ variable, is positive and significant, as expected, with a magnitude around 9%, in line with the range reported by Card *et al.* (2018), suggesting that wages are somewhat responsive to productivity shocks. Finally, we can see our main object of interest, the estimated β_{w3}, to be negative and significant, with magnitude −0.71%. Positive productivity effects accompanying a firm's involvement in FNAs are thus not transferred to workers. Not only that, the negative coefficient indicates that such productivity effects within FNAs even

TABLE 9 Rent-sharing equations—PSM sample.

	Overall sample	Unionization rate		Relative average wage	
		High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)
FNA_{jit}	−0.34%***	−0.35%***	−0.52%***	−0.13%	−0.38%***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\hat{\xi}_{jit}$	+9.63%***	+9.22%***	+9.18%***	+9.31%***	+8.48%***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
$FNA_{jit} \times \hat{\xi}_{jit}$	−0.71%***	−0.42%	−1.09%***	−0.93%***	−1.08%***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Observations	7,245,911	3,268,467	3,977,444	2,832,961	4,183,529

Notes: Dependent variable: $Wage_{jit}$. Worker-level data. Standard errors (in parentheses) are clustered at the worker level. $\hat{\xi}_{jit}$ is the innovation in the productivity level obtained from the ACF-FE estimation of a standard log-linearized Cobb–Douglas production function, with employees (log) and capital (log) as inputs, and added controls for size (five classes), industry (three-digit ATECO 2007 classification), province and year fixed effects, plus year–industry and year–province interactions. We also include, among controls, the capital-to-labour ratio (log). It is defined as the natural logarithm of capital over employees. Capital is measured by the physical capital stock (i.e. tangible fixed assets), computed through the permanent inventory method applied by Card *et al.* (2014). It applies a constant depreciation rate equal to 0.065; the benchmark in the first year is given by the book value of fixed assets. As direct information on investments is unavailable in our data, these are computed as the difference between fixed assets in two contiguous years. All the estimations are based on specification Job-match FE of Table 7.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

damage workers' wages, hindering their wage increases compared to those workers outside networks. In other words, more than a rent-sharing effect, we detect a 'rent-appropriating' effect, which may be indicative of an increased monopsonistic power enhanced by FNAs.

Columns (2)–(5) of Table 9 present the outcomes concerning the subsamples identified by the proxies for workers' bargaining power. This rent-appropriating effect becomes more pronounced in circumstances where workers' relative bargaining power is diminished, specifically when the unionization rate and workers' relative wage are low. For instance, although negative, the estimated β_{w3} is statistically insignificant in contexts with a high unionization rate. Conversely, in situations characterized by a low unionization rate, it becomes significantly negative and substantial in magnitude, amounting to −1.09%.[27]

In summary, the evidence from rent-sharing estimations reinforces the understanding of FNAs as mechanisms that, while enhancing firm performance, typically fail to result in higher wages for workers. This raises questions about whether FNAs serve as tools for bolstering firms' monopsonistic positions and their bargaining power at the expense of workers. However, it is important to note that we focus on wages, without considering other potential outcomes for workers, such as positive reallocation effects or career advancements resulting from FNAs. Establishing a more global effect of FNAs on workers deserves other efforts, which should be pursued in future research.

7 | CONCLUSIONS

By exploiting extensive administrative matched employer–employee panel data, this paper provides novel evidence on the impact of inter-firm cooperation on both firms and workers. We focus on an innovative policy instrument introduced in Italy in 2009, the formal network agreement. This instrument allows firms to co-produce, co-market, co-purchase, or cooperate in product or market development through specific contractual agreements. Such contracts, in line with the classical definition of inter-firm networks, were introduced by policymakers with the primary aim of enhancing the competitiveness of small businesses.

Our study makes several contributions to the literature. First, we offer new insights into the impacts of formal networks on firms. Our firm-level analysis covers the entire population of private-sector incorporated companies in Italy over a decade, controlling for major sources of endogeneity. This provides a robust and large-scale assessment of network impacts on firms. We evaluate multiple performance indicators, including labour and total factor productivity (TFP). To address concerns about firms' strategic decisions to enter networks, we employ a difference-in-differences (DiD) estimator alongside propensity score matching techniques, supplemented by various alternative methods such as instrumental variable and one-step control function estimations. Our findings align with prior empirical evidence, indicating positive returns from inter-firm cooperation for firms. Specifically, we observe significant and economically meaningful improvements in both labour and TFP, as well as profitability. Moreover, our analysis reveals substantial heterogeneity in these impacts, with smaller firms in economically disadvantaged areas and with lower initial productivity experiencing stronger performance gains. This suggests that the network contract aligns with its original policy intent.

From the worker-level perspective, our paper breaks new ground by exploring the impact of employers' cooperation on workers' wages, and analysing the existence of productivity-wage pass-through mechanisms. Using DiD wage regressions in conjunction with propensity score matching techniques, we provide compelling evidence that over our sample period, the benefits observed at the firm level are not passed on to workers. This finding is corroborated by results from rent-sharing regressions, indicating that formal networking among employers slightly compresses their employees' wages. However, our analysis reveals substantial variation in wage effects across different types of firms, aligning with the primary goals of the policy instrument and theoretical predictions. In contrast to the overall effect, we find modest positive wage impacts for small firms, those that are less productive, and located in less developed areas. In these contexts, where performance advantages are more pronounced, there is a partial transfer of benefits to workers. Conversely, we find negative wage effects in firms that are more competitive and possess higher bargaining power—specifically, larger firms located in affluent areas and characterized by high productivity. In such contexts, the positive benefits on the employer side are not shared with employees, and indeed wages are reduced. Moreover, we find that the presence of unions substantially limits the compression of wages, by counterbalancing the additional power in the wage-setting process derived from employer cooperation.

Our evidence raises concerns that without introducing mechanisms to compensate workers for their losses in bargaining power and outside opportunities, formal networks among firms may enhance their monopsonistic power. Recent actions have begun to address this imbalance. During the Covid-19 downturn, the network agreement was utilized to foster solidarity among firms, formalizing cooperation with the specific goal of preserving employment levels.[28] Consequently, the network contract has emerged as a potentially significant instrument for supporting both firms and workers during crises. Policymakers should continue efforts to ensure that the benefits derived from formal networks are shared equitably between firms and workers. First, in defining the goals and objectives of formal networks, greater attention should be given to specifying the anticipated benefits for workers, explicitly incorporating them into the cooperation justification. Analysing the declared goals and programmes of networks using text-mining techniques can assist in evaluating these aspects. Second, mechanisms for rent-sharing should be facilitated. Promoting and incentivizing decentralized bargaining at the network level (e.g. through tax incentives) should be a cornerstone of formal inter-firm cooperation. Additionally, promoting unionization within networked firms could help to mitigate the potential loss of workers' bargaining power.

ACKNOWLEDGMENTS

We gratefully acknowledge the data access provided by the VisitINPS programme. We would like to thank Edoardo Di Porto and Paolo Naticchioni for their general help with INPS data usage. We thank the Editor, the Associate Editor, and an anonymous reviewer for their helpful comments. Thanks are also due to Ainoa Aparicio Fenoll, Christopher J. Flinn, Lorien Sabatino, and participants in various seminars and conferences. The authors gratefully acknowledge the financial support of MIUR—Ministry of Education, University and Research (Financing Fund for Departments of Excellence), Italy. The opinions expressed by the authors are solely their own and do not necessarily represent the views of INPS. Open access publishing facilitated by Università degli Studi di Torino, as part of the Wiley - CRUI-CARE agreement.

ENDNOTES

[1] In Italian, the word 'rete' translates to 'network'. Consequently, 'contratto di rete' can be rendered as 'network contract' in English.

[2] Cisi *et al.* (2020) and Burlina (2020) provide detailed reviews comparing the evidence by different definitions of network and by measures of performance.

[3] The description of FNA's programmes and goals are freely available in text format and should be managed according to text-mining techniques. The recent contribution by Caragliu and Landoni (2024) is the first attempt in this direction. They classify networks into six groups using textual analysis, and find that contracts finalized to R&D and to collect public funding have a higher impact on profits.

[4] This register can be downloaded freely from https://contrattidirete.registroimprese.it/reti (accessed 18 September 2024).

[5] The restriction on consecutive observations is a necessary condition to estimate TFP through the control function method described below.

[6] This random sample was obtained starting from the sample of firms. We selected 20% of them and then considered the employees working in such firms in each year.

[7] Unless explicitly indicated, we always consider employees in full-time equivalents (FTEs).

[8] For workers on part-time contracts, we have direct information on the number of hours stipulated by the contract, which we use to re-proportion the wage of part-timers to be fully comparable to the wage of full-timers. This information was obtained from the INPS variable called 'settimane utili'.

[9] The FNA_{jit} variable has the same pattern, as long as the worker stays in the same firm. In the case of a change of employer, let us say firm k, the worker-level variable has attached the value FNA_{kt}.

[10] We pursued robustness tests by considering a different definition of FNAs dummies, which reflects the five-year expiration rule. These alternative dummies thus switch back to 0 after five years from the creation of an FNA. As expected, the results, on both the firm and worker sides, remain unchanged.

[11] Moreover, the probability of engaging in business alliances, and then participating in network agreements, is strongly influenced by the quality of corporate governance or by the ability of the managers (or of the owners, in the case of SME), as argued by Bodnaruk *et al.* (2013).

[12] Concerning the impact on TFP, we perform an additional robustness test. We estimate, within the ACF-FE framework, a production function augmented with FNA_{it}, and insert it among the set of endogenous variables. Technical details are provided in Appendix Subsection A.2, and the results are presented in Subsection 6.1.

[13] We impose a common support to the treated firms. Moreover, to ensure a more efficient matching, we require both the treated and control firms to be observed in 2018.

[14] The predicted probabilities are time-invariant, since they derive from an estimation of the probability of joining an FNA during the observation window based on 2008 and 2009 regressors.

[15] We retrieve the necessary information from the INPS 'firm archive', which provides information on all such organizations that have employees.

[16] There is evidence that social trust can influence the performance of firms operating in the local community, which would limit the validity of our instrument. However, social trust is conceived as a wide concept, encompassing several dimensions, such as the efficiency of institutions and the presence of active participation of people in society (Vanneste and Gulati 2022). On the contrary, our instrument is limited to capturing one particular aspect of social cohesion, measured at the municipality level, so that the potential connections with firm-level outcomes are likely weaker.

[17] While such aspects may vary over time, the η_i variable captures important average tendencies. Moreover, features related to a firm's culture are rather persistent and traditionally assumed to be fixed over a relatively short time horizon like our panel (Guiso *et al.* 2015).

[18] We cannot account for the worker's education explicitly, as this information cannot be obtained from our data. However, this should not represent an issue, as education is mostly time-invariant for those who are employed and is therefore largely accounted for by worker fixed effects (see also Connolly and Gregory 2008).

19 The estimates of the β_p coefficients of equation (2) are to be interpreted as the difference in the considered performance indicator obtained from being a member of an FNA as compared with the specific control group of firms.
20 While OLS (and FE) estimation delivers estimates of the average treatment effect over the entire population, IV estimation (with valid and relevant instruments) can identify local average treatment effects.
21 In Appendix Subsection A.5, we present several robustness checks on the firm-level analysis. In particular, (i) we test the sensitivity of our findings to the exclusion of crisis years, (ii) we experiment with the inclusion of additional interaction fixed effects, and (iii) we perform an alternative PSM approach that includes more explicitly pre-trends in the outcome variables among the set of variables used to identify the PSM sample.
22 The estimates of the β_w coefficient of equation (3) are to be interpreted as the difference in the wage of workers that are involved in an FNA (i.e. their employer is a member of an FNA) as compared with the specific control group of workers. Therefore a negative estimate of β_w should be conceived not as an absolute decrease in the wages of workers experiencing FNAs, but as a decrease relative to the wages of workers not experiencing FNAs. This is relevant for the interpretation of results, particularly considering the tendency of downward wage rigidity in the Italian labour market (Devicienti *et al.* 2007).
23 In Appendix Subsection A.5, we discuss several robustness checks conducted on the worker-level analysis. In particular, (i) we test for the sensitivity of results excluding the years surrounding the Great Recession, (ii) we experiment with different threshold levels for selecting the block random sample, and (iii) we perform a double-PSM procedure, which consists of carrying out a second PSM at the worker level to identify the PSM sample of workers.
24 These worker-level analyses, along with subsequent analyses, are conducted on the PSM samples using the preferred specification Job-match FE.
25 Typically, a specific CCNL applies to all employees within a firm.
26 See Subsection 3.3 and Appendix Subsection A.1 for details.
27 The difference in the two coefficients from the estimations based on the level of relative average wage, though lower, is statistically significant at conventional levels.
28 The 'solidarity goal' has been added by Law no. 77/2020 to the list of goals that network contracts should define in their declaration upon constitution.
29 Such a method would deliver consistent estimates only under two strong assumptions: (i) the omitted variable bias derives exclusively from unobserved time-invariant variables; and (ii) inputs do not respond to unobserved productivity fluctuations.
30 The ACF estimator is part of the larger family of the so-called 'control function estimators' (CFEs), introduced by the seminal work of Olley and Pakes (1996). These CFEs are widely used in applied studies and represent the standard way of estimating firm-level production functions to date (Ackerberg *et al.* 2015).
31 For the sake of simplicity, we omit the terms that include the basic control dummies (i.e. size, industry, province and year fixed effects, as well as year–industry and year–province interactions) from equation (A2). The ω_{it} term thus reflects the unobserved firm-specific productivity level once these fixed effects, which may be correlated with the inputs, are removed.
32 Note that these are just the predicted values from the regression in equation (A6).
33 They also include the constant term α, which eventually does not matter.
34 It applies a constant depreciation rate equal to 0.065; the benchmark in the first year is given by the book value of fixed assets. As direct information on investments is unavailable in our data, this is computed as the difference between fixed assets in two contiguous years.
35 For the sake of simplicity, we omit the terms that refer to our control variables from equation (A2). In this setting, we control for a wide array of firm- and workforce-level characteristics, which include: the firms' age; workforce shares by gender, origin, age, job contract type, job contract duration and job contract working time; and size, industry (three-digit ATECO 2007 classification), province and year fixed effects. The ω_{it} term thus reflects the unobserved firm-specific productivity level once these variables are taken into account.
36 Estimation of augmented production functions with CFEs, such as ACF-FE, is a commonly and widely used way to solve endogeneity problems related to the variable of interest, such as FNA in our case. Among others, studies have analysed the productivity impact of sickness absenteeism (Grinza and Rycx 2020), workers' flows and reallocation dynamics (Grinza 2021), and training (Konings and Vanormelingen 2015), as well as the existence of learning-by-hiring effects (Parrotta and Pozzoli 2012).
37 We have run these estimates with alternative estimation methods, including FE regressions without the PSM restriction (i.e. starting from the full sample) and CF regressions, as in panel C of Table 6. The results are in line with those reported here, and are available on request.

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How to cite this article: Devicienti, F., Grinza, E., Manello, A. and Vannoni, D. (2024). Employer cooperation, productivity and wages: new evidence from inter-firm formal network agreements. *Economica*, 1–41. https://doi.org/10.1111/ecca.12553

APPENDIX A

A.1 Estimation of TFP

A critical issue in the estimation of production functions is the simultaneity of inputs; that is, inputs are endogenous since they respond to a firm's productivity level unobserved by the econometrician. For example, a highly productive firm likely produces more, thus using more inputs. Similarly, a productivity improvement (e.g. due to the introduction of a process innovation) may lead to an increase in the usage of inputs. This simultaneity problem makes the OLS estimates of the input contributions—and consequently of TFP—inconsistent. A fixed effects (FE) estimation (Mundlak 1961) cannot solve the issue either, although it removes the time-invariant components of a firm's productivity.[29] Therefore a method is needed that can control for a more articulated framework, whereby productivity can fluctuate over time, and production inputs are allowed to respond to such fluctuations.

The ACF method represents a solution to simultaneity. In a nutshell, Ackerberg *et al.* (2015) use a firm's demand for intermediate inputs to proxy for its unobserved productivity. The rationale is that intermediate inputs can capture unobserved productivity because firms can easily adjust their use of intermediate inputs in response to productivity shocks.[30] In this paper, we use a modified version of the ACF method, that is, ACF-FE. This version was developed recently by Lee *et al.* (2019) and extends the ACF procedure to account explicitly for firm fixed effects. This is relevant because substantial and persistent differences in productivity levels have been found ubiquitously in the data (Syverson 2011). Explicitly accounting for firm fixed effects thus ensures that firm-specific persistencies in productivity levels are controlled for. Moreover, it improves the ability of the proxy variable to capture fluctuations in unobserved productivity.

We here present a discussion on our empirical framework for estimating TFP in the context of ACF-FE estimation. For other details on the underlying assumptions (which we summarize here) and their implications, the reader may refer to Ackerberg *et al.* (2015) and Lee *et al.* (2019).

We estimate the production function

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k}. \tag{A1}$$

We model the residual productivity A_{it} as

$$A_{it} = exp\{\alpha + \omega_{it} + \varepsilon_{it}\}, \tag{A2}$$

where α is the average productivity of the firms, and ω_{it} is the time- and firm-specific (i.e. idiosyncratic) productivity level, whereas ε_{it} is a transitory shock.[31]

In practice, the production function that we estimate is obtained by using equation (A2) and by taking logarithms in equation (A1):

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it}, \tag{A3}$$

where lowercase letters indicate logarithms.

First, it is assumed that the firm's information set at t, I_{it}, includes both the current and past productivity levels, $\{\omega_{i\tau}\}_{\tau=0}^{t}$, but not the future productivity levels, $\{\omega_{i\tau}\}_{\tau=t+1}^{\infty}$. Furthermore, it is assumed that the transitory shock ε_{it} is not predictable by the firm (i.e. $E[\varepsilon_{it}|I_{it}=0]$).

Second, it is assumed that the unobserved productivity level ω_{it} evolves according to the distribution

$$p(\omega_{it+1}|I_{it}) = p(\omega_{it+1}|\omega_{it}), \tag{A4}$$

which is known to the firm. Equation (A4) expresses the concept that the productivity level evolves according to a first-order Markov process.

These two assumptions imply that it is possible to decompose ω_{it} into its conditional expectation at $t-1$ and an innovation term

$$\omega_{it} = E[\omega_{it}|I_{it-1}] + \xi_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it} = g(\omega_{it-1}) + \xi_{it},$$

where, by construction, $E[\xi_{it}|I_{it-1}]=0$. Hence $g(\omega_{it-1})$ is that part of ω_{it} that the firm can predict at $t-1$, whereas ξ_{it} is the innovation in ω_{it} observed by the firm at t and, by construction, not predictable at $t-1$. In practice, firms observe ω_{it} at t and construct expectations on ω_{it} at $t-1$ by using $g(\cdot)$.

An example may help to clarify this framework. Let us suppose that the firm is experiencing a productivity boom, that is, a series of positive productivity shocks. This is compatible with, for instance, any technological progress introduced into the firm (e.g. a new process technology). The set of assumptions outlined above implies that the firm knows the past and current productivity enhancements that it is experiencing. It also implies that the firm is able to predict, with a certain degree of error, the next period's productivity level on the basis of the current productivity level.

Third, it is assumed that firms accumulate capital according to

$$k_{it} = \kappa(k_{it-1}, i_{it-1}),$$

where investments i_{it-1} are chosen at $t-1$. This implies that the firm decides upon the level of capital to use at t one period earlier, at $t-1$ (i.e. $k_{it} \in I_{it-1}$). This assumption entails that it takes a full period for new capital to be ordered, delivered and installed. Moreover, it implies that capital has dynamic implications (i.e. the firm's choice of capital for period t has an impact on its future profits). We assume that labour at t is chosen as capital, one period earlier, thereby allowing it to have dynamic implications. This assumption is consistent with the presence of significant labour market rigidities in the Italian labour market (e.g. rigid employment protection legislation) and is often adopted in the literature (see, for instance, Konings and Vanormelingen 2015).

Fourth, it is assumed that the firm's demand for intermediate inputs, m_{it}, is a function of labour, capital, and the firm's unobserved productivity level:

$$m_{it} = f(l_{it}, k_{it}, \omega_{it}). \tag{A5}$$

Finally, it is assumed that the function in equation (A5) is strictly increasing in ω_{it}. Conditional on labour and capital, the higher the unobserved productivity level, the larger the demand for intermediate inputs.

At this point, Ackerberg *et al.* (2015) outline a two-step estimation method. Given the assumptions discussed above, f can be inverted to deliver an expression of ω_{it}, which is unobservable, as a function of l_{it}, k_{it} and m_{it}, which are instead observable:

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, m_{it}).$$

The inverted intermediate input demand function $f^{-1}(\cdot)$ is the key to control function estimators (CFEs): it allows us to 'control' for the unobserved productivity level once it is plugged into the production function. Hence substituting $f^{-1}(\cdot)$ in equation (A3) results in the first-stage equation

$$\begin{aligned} y_{it} &= \alpha + \beta_l l_{it} + \beta_k k_{it} + f^{-1}(l_{it}, k_{it}, m_{it}) + \varepsilon_{it} \\ &= \Phi(l_{it}, k_{it}, m_{it}) + \varepsilon_{it}. \end{aligned} \tag{A6}$$

As is common in the literature, we proxy the $f^{-1}(\cdot)$ function with a third-order polynomial in l_{it}, k_{it} and m_{it} (Ackerberg *et al.* 2015). The β_l and β_k parameters are not identified at this stage and are subsumed in $\Phi(l_{it}, k_{it}, m_{it}) = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it}$. However, the estimation of equation (A6) produces an estimate $\widetilde{\Phi}(l_{it}, k_{it}, m_{it})$ of $\Phi(l_{it}, k_{it}, m_{it})$.[32] Given the guesses of β_l and β_k, denoted as β_l^* and β_k^*, respectively, it is possible to recover the implied ω_{it}, $\widetilde{\omega}_{it}(\beta_l^*, \beta_k^*)$,[33] as

$$\widetilde{\omega}_{it}(\beta_l^*, \beta_k^*) = \widetilde{\Phi}(l_{it}, k_{it}, m_{it}) - \beta_l^* l_{it} - \beta_k^* k_{it}. \tag{A7}$$

As ω_{it} is assumed to follow a first-order Markov process (i.e. $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$), and given $\widetilde{\omega}_{it}(\beta_l^*, \beta_k^*)$, it is possible to compute the implied innovations $\widetilde{\xi}_{it}(\beta_l^*, \beta_k^*)$ as the residuals of a regression of $\widetilde{\omega}_{it}(\beta_l^*, \beta_k^*)$ on $g(\widetilde{\omega}_{it-1}(\beta_l^*, \beta_k^*))$. Following standard practice, we proxy the function $g(\cdot)$ with a third-order polynomial in $\widetilde{\omega}_{it-1}(\beta_l^*, \beta_k^*)$ (Lee *et al.* 2019). The second step of the procedure now recovers the parameters of interest by evaluating the sample analogues of the moment conditions that stem from the previously stated timing assumptions:

$$\frac{1}{N}\,\frac{1}{T}\sum_i\sum_t \widetilde{\xi}_{it}(\beta_l^*, \beta_k^*)\; k_{it} = 0, \qquad \frac{1}{N}\,\frac{1}{T}\sum_i\sum_t \widetilde{\xi}_{it}(\beta_l^*, \beta_k^*)\; l_{it} = 0. \tag{A8}$$

The search continues over β_l^* and β_k^* until the $\widetilde{\beta}_l$ and $\widetilde{\beta}_k$ that satisfy equations (A8) are found. These are the ACF estimates of β_l and β_k.

The ACF-FE estimator involves only a minimal modification of the standard ACF method, which can be outlined as follows. All the assumptions of ACF are maintained, except for the assumption on the stochastic process that regulates unobserved productivity, which is generalized in the ACF-FE setting. In particular, ω_{it} is assumed to follow a first-order Markov process conditional on a time-invariant random variable η_i:

$$\omega_{it} = E[\omega_{it} | \omega_{it-1}, \eta_i] + \xi_{it}, \tag{A9}$$

where $E[\xi_{it} | \omega_{it-1}, \eta_i] = 0$ and $E[\varepsilon_{it} | \eta_i = 0]$. In particular, Lee *et al.* (2019) consider a version of equation (A9) where $E[\omega_{it} | \omega_{it-1}, \eta_i] = \eta_i + g(\omega_{it-1})$, which results in

$$\omega_{it} = \eta_i + g(\omega_{it-1}) + \xi_{it}. \tag{A10}$$

The first step of the ACF-FE procedure, for the above specification of ω_{it}, is the same as in ACF, except for the addition of the fixed-term effect η_i. It is still possible to estimate $\Phi(\cdot)$ from the analogue of equation (A6) with added firm fixed effects. In the second stage, it is possible to estimate β_l and β_k by proceeding as before, but this time including η_i in the stochastic process of the unobserved productivity level, as defined in equation (A10), thereby recovering the implied ω_{it} as in equation (A7), and then the implied ξ_{it}, as the residuals from an FE regression of $\widetilde{\omega}_{it}$ on $g(\widetilde{\omega}_{it-1})$, with $g(\cdot)$ being approximated with a third-order polynomial (Lee *et al.* 2019).

In our empirical analysis, output (Y_{it}) is measured with value-added, whereas the labour input (L_{it}) is expressed as the number of employees. We measure capital (K_{it}) starting from tangible fixed assets and adopting the version of the permanent inventory method implemented by Card *et al.* (2014).[34] The demand for intermediate inputs is measured by the intermediate input items of the profit and loss statement, which include intermediate goods and services used in the production process. We estimate a separate production function for each two-digit ATECO 2007 industry. This allows us to take into account any structural differences in the production processes and technologies among different economic sectors. In total, we thus pursue the ACF-FE estimation of 67 different production functions. All these estimations include controls for size, industry (three-digit ATECO 2007 classification), province and year fixed effects, as well as year–industry and year–province interactions. In sum, our TFP estimates are the residuals from the ACF-FE estimation of these sector-specific production functions.

A.2 Endogenizing FNAs: one-step ACF-FE estimation

When assessing the impact of FNAs on TFP, one method to solve endogeneity issues related to FNAs (together with input simultaneity) is to perform the ACF-FE estimation of a production function augmented with the FNA variable.

The reference production function is the same as in equation (A1), except that the residual productivity A_{it} is now modelled as

$$A_{it} = \exp(\alpha + \beta_p \ FNA_{it} + \omega_{it} + \varepsilon_{it}).$$

As before, α is the average productivity of the firms, ω_{it} is the idiosyncratic productivity level, and ε_{it} is the transitory shock. The FNA_{it} variable is now modelled directly within the expression for TFP, and the coefficient β, our object of interest, captures the impact of a firm's participation in an FNA on TFP.[35] In sum, the production function that we estimate is

$$y_{it} = \alpha + \beta_l \ l_{it} + \beta_k \ k_{it} + \beta_p \ FNA_{it} + \omega_{it} + \varepsilon_{it},$$

where lowercase letters indicate logarithms.

All the assumptions described in Subsection A.1 are maintained. In addition, here it is assumed that a firm's participation in an FNA in year t is decided, as for labour and capital inputs, one year before, at $t-1$. The FNA_{it} variable is then inserted among the set of endogenous variables in the model, which implies that

$$m_{it} = f(l_{it}, k_{it}, FNA_{it}, \omega_{it}).$$

Starting from this equation, all the formulae in Subsection A.1 are thus adapted to include the FNA dummy. Together with estimates of β_l and β_k, the ACF-FE estimation procedure also delivers an estimate of β, our object of interest, obtained from the moment condition[36]

$$\frac{1}{N} \ \frac{1}{T} \sum_i \sum_t \widetilde{\xi}_{it}(\beta_l^*, \beta_k^*, \beta^*) \ FNA_{it} = 0.$$

A.3 Heterogeneities in the impact of FNAs on firm performance

In this subsection, we investigate the role of firms' location, size, and relative productive performance, hypothesizing that these factors may modulate the effects of FNAs on firm performance. By examining these dimensions, we thus aim to unravel the differential implications of participation in FNAs, providing insights into how various contextual factors shape the impact of interest. The results of these analyses are reported in Table A1. We estimate a separate regression for each category of firms (i.e. our regressions are run on split samples). We consider as dependent variables the usual performance indicators, that is, TFP, labour productivity and profitability. All of these estimates are obtained by applying the preferred PSM-DiD estimation, as in panel B of Table 6. Therefore these estimates refer to (various subsamples of) the PSM sample.[37]

The first hypothesis is that the positive performance impact of FNAs may be greater for firms facing more pronounced disadvantages. Involvement in FNAs might yield heightened benefits in less developed areas, where resource, information and knowledge sharing can serve as a practical strategy to counteract isolation and compensate for deficient infrastructure and service provisions. To evaluate this, we look at the geographical location of the firms. Panel A of

TABLE A1 Heterogeneities in the effects of FNAs on firm performance—PSM sample.

	Dependent variable			
	TFP	Labour productivity (log)	Profitability (log)	Observations
	(1)	(2)	(3)	(4)
Panel A: Macro-area				
North-west	+0.019*	+0.025**	+0.034	69,561
	(0.011)	(0.011)	(0.029)	[64,754]
North-east	+0.015*	+0.019**	+0.014	75,772
	(0.009)	(0.009)	(0.024)	[70,800]
Centre	+0.014	+0.019	+0.045	43,115
	(0.012)	(0.012)	(0.031)	[40,070]
South and islands	+0.055***	+0.064***	+0.109***	30,935
	(0.015)	(0.014)	(0.034)	[28,892]
Panel B: Size				
5–9 employees	+0.022	+0.025	−0.003	30,367
	(0.019)	(0.018)	(0.046)	[28,319]
10–19 employees	+0.027***	+0.035***	+0.054**	75,753
	(0.010)	(0.010)	(0.024)	[70,898]
20–49 employees	+0.020**	+0.024***	+0.025	76,991
	(0.008)	(0.008)	(0.025)	[71,843]
50–249 employees	+0.007	+0.012	+0.042	35,176
	(0.010)	(0.010)	(0.033)	[32,412]
250+ employees	+0.001	+0.010	−0.081	1096
	(0.023)	(0.025)	(0.114)	[1044]
Panel C: TFP quartile				
First quartile	+0.044***	+0.064***	+0.137***	24,345
	(0.017)	(0.017)	(0.049)	[17,455]
Second quartile	+0.003	+0.008**	−0.028	45,123
	(0.003)	(0.004)	(0.026)	[41,164]
Third quartile	+0.006**	+0.010***	+0.025	66,303
	(0.003)	(0.004)	(0.019)	[63,746]
Fourth quartile	+0.021***	+0.021***	+0.038**	83,612
	(0.007)	(0.007)	(0.019)	[82,151]

Notes: Firm-level data. Standard errors (in parentheses) are clustered at the firm level. TFP quartiles are computed on the yearly distributions of TFP in the full sample. All the estimations are based on specification PSM-DiD of Table 6. In square brackets, we report the number of observations for the estimations in column (3).
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

Table A1 presents regression results across the four Italian macro-areas: north-west, north-east, centre and south of Italy, encompassing island regions (i.e. Sardinia and Sicily). Italy is marked by substantial economic and infrastructural differentials among these macro-areas, offering a lens into how external socioeconomic and technical environments might modulate the impact of FNAs on firm performance. Notably, the south of Italy is the most peripheral area, characterized by inadequate infrastructure and service provisions for firms, whereas the centre represents an intermediate scenario, and the north-east and north-west stand out as the most developed areas. As expected, the table reveals heterogeneous effects across macro-areas. While the impacts on TFP and labour productivity are generally positive and significant, the south is characterized by substantially heightened impacts, ranging from 5.5% to 6.4% for TFP and labour productivity, respectively. Notably, a significantly positive impact on profitability is discerned solely in the south of Italy (+10.9%). Confirming our hypothesis, this pattern suggests that while positive effects of FNAs are observable across all the geographical areas, they appear markedly amplified in more disadvantaged regions.

Firm size emerges as a crucial aspect influencing the scope, objectives and potential outcomes of participation in FNAs, as well as the relevance of competition and market power issues related to firms' formal networking activities. The second hypothesis that we want to test is that the performance impact of FNAs varies across firm size. In particular, we posit that smaller firms benefit more from participation in FNAs because FNAs allow them to leverage the economies of scope and scale afforded by larger firms, while preserving the flexibility inherent in their organizational structure. To examine these effects, we categorize firms into five size classes based on the number of employees, and examine the performance effects of FNAs across each category. As shown in panel B of Table A1, the impact of FNAs on firm performance exhibits notable diversity across firm size. Confirming our hypothesis, positive and significant effects on productivity and profitability are discernible primarily among smaller firms (ranging from 10 to 49 employees for TFP and labour productivity, and specifically within the 10–19 employees category for profitability). The estimated effects on productivity for small firms fall within the range 2.0–2.7% for TFP and 2.4–3.5% for labour productivity. The findings underscore substantial heterogeneity across firm size, with positive effects of FNAs observed mainly among smaller firms, which constitute a predominant component of the Italian industrial landscape.

Finally, we distinguish firms based on their productive performance, intending to test the presence of differentiated effects for more and less productive companies. We hypothesize that FNAs yield heightened benefits for firms with lower productivity levels, representing a more disadvantaged segment of the market. Such firms can gather relatively more benefits from FNAs, for instance, leveraging knowledge spillovers from other network participants, and finding an external push to make their processes and operations more efficient. To evaluate this, we first classify firms according to the four TFP quartiles. Notably, these quartiles are identified on the yearly distributions of TFP in the full sample (i.e. not on the PSM sample). One should conceive, for instance, the firms in the first quartile as those least productive in comparison to the whole sample, and not with reference to the PSM sample. We then run our usual set of estimations on the four subsamples identifying the various productivity levels. The results are reported in panel C of Table A1. While positive and significant performance impacts are widespread across the productivity distribution, as hypothesized, we detect substantially stronger effects for the first TFP quartile, that is, the least productive firms. For these companies, involvement in FNAs is predicted to increase TFP and labour productivity by as much as 4.4% and 6.4%, respectively, and profitability by an even larger amount, that is, 13.7%. This result thus supports our hypothesis, suggesting that FNAs serve as a particularly potent mechanism for empowering firms operating at the margins of productivity, where access to external knowledge and resources via network participation can catalyse significant improvements in performance outcomes.

A.4 Heterogeneities in the impact of FNAs on wages

In this subsection, we present the results of the heterogeneity analysis on workers. We first explore whether the effect of FNAs on wages is differentiated across job contract type. We then evaluate the presence of heterogeneities across workers employed in different firms, based on their location, size and TFP quartile. These three-letter subdivisions retrace the categories explored in the firm-level heterogeneity analysis discussed in Subsection A.3. We estimate the effects on the split samples—that is, we conduct separate estimations for each category of workers analysed. All of the estimations are based on specification Job-match FE of Table 7, and concentrate on

TABLE A2 Heterogeneities in the effects of FNAs on wages—PSM sample.

			Observations
Panel A: Job contract type			
Low-skilled	−0.37%***	(0.001)	4,629,366
High-skilled	−0.11%	(0.001)	2,616,545
Panel B: Macro-area			
North-west	−0.99%***	(0.001)	2,365,144
North-east	−0.59%***	(0.001)	2,437,944
Centre	+0.28%***	(0.001)	1,392,568
South and islands	+1.34%***	(0.002)	1,050,255
Panel C: Size			
5–9 employees	−0.38%	(0.004)	230,059
10–19 employees	+0.53%***	(0.002)	1,076,208
20–49 employees	+0.19%*	(0.001)	2,454,176
50–249 employees	−0.66%***	(0.001)	3,084,950
250+ employees	+1.51%***	(0.003)	400,518
Panel D: TFP quartile			
First quartile	+1.78%***	(0.003)	605,584
Second quartile	−0.00%	(0.002)	1,184,875
Third quartile	−0.05%	(0.001)	2,155,032
Fourth quartile	−0.57%***	(0.001)	3,300,420

Notes: Dependent variable: $Wage_{jit}$. Worker-level data. Standard errors (in parentheses) are clustered at the worker level. Low-skilled job contract types include blue-collar workers and apprentices, whereas high-skilled job contract types include white-collar workers, middle managers and top managers. All the estimations are based on specification Job-match FE of Table 7.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

the (split samples of the) PSM sample. The results are shown in Table A2. Overall, they show that the effect on wages is not homogeneous, but that negative effects are concentrated on specific categories of workers, while hiding positive and significant impacts on others.

First, the subdivision across job contract type categorizes low-skilled and high-skilled workers. The former includes blue-collar workers and apprentices, whereas the latter encompasses white-collar workers, middle managers and top managers. From panel A of Table A2, it appears that the negative effects concentrate on low-skilled workers. For high-skilled workers, the impact of FNAs on wages, while negative, is not significant. This finding suggests that the rent-appropriating mechanism might be stronger for the weaker segments of the labour market, that is, categories of workers more typically characterized by lower bargaining power.

Second, looking at the macro-area, the wage effects are polarized (panel B of Table A2). Workers in the north of Italy display significant negative effects, with a relatively large magnitude (−0.99% and −0.59% in the north-west and north-east, respectively). In northern areas, the overall finding of positive effects for firms that are not transferred to the workers in the form of wage increases is thus confirmed. The wage effects are opposite in the centre and the south of Italy. In southern regions, in correspondence with benefits for the firms from FNAs, significant positive impacts on workers' wages are observed. However, we should note that the positive effects on the workers in such an area are accompanied by substantially higher positive effects on firm performance as compared with firms located in northern regions, where the effects on performance are typically less intense. This evidence might be suggestive of the fact that if performance benefits surpass a certain threshold, also workers can start gaining from FNAs.

Third, we consider firm size. Again, we detect substantial heterogeneities in the impact of FNAs on wages. Micro firms, with fewer than 9 employees, are associated with a non-significant wage effect, which reflects what we observe for firm performance (no effect on either productivity or profitability). If we consider small firms (10–19 and 20–49 employees subclasses), then we detect positive impacts on wages, particularly for the former category (+0.53%). Notably, such categories of firms are detected to experience the highest benefits in terms of firm performance, particularly productivity. Instead, the overall negative wage impact seems to be driven by medium-sized businesses, with 50–249 employees. This category collects the highest number of workers, amounting to around 43% in the PSM sample. Finally, for large firms, with more than 250 employees, we detect a significantly positive effect (+1.51%). This effect on large firms' workers comes along with a substantially zero effect on the performance of such firms.

Finally, Table A2 considers the subdivisions across the firms' TFP quartiles, which are derived as explained in Subsection A.3. Here, we can see polarized effects of FNAs on wages. A significant positive wage impact is observed for low-productivity firms (first quartile), which are estimated to obtain the highest performance benefits. On the contrary, a significant negative impact is detected for highly productive firms, whereas no effects on workers in firms with intermediate productivity levels (second and third quartiles) are observed.

A.5 Robustness checks

In this subsection, we discuss several robustness checks performed on both the firm- and worker-level analyses.

A.5.1 Excluding crisis years

It is important to consider whether FNAs might operate differently during crisis years as compared to more stable economic periods. In fact, FNAs could potentially function differently during times of economic turbulence, due to shifts in market conditions and firms' responses to economic uncertainty, thereby affecting firms and workers differently.

We have thus conducted robustness checks to evaluate the outcomes, at both the firm and worker levels, across various subperiods, excluding the years surrounding the Great Recession. Through these analyses, we aim to ascertain whether the effects of FNAs on firm productivity and workers' wages persist consistently across various economic conditions. Specifically, we analysed distinct subperiods, including 2015–18, 2013–18, 2012–18 and 2010–18, and conducted the main analyses on firm productivity (including TFP and labour productivity) and workers' wages within each of these subsamples. Our findings indicate consistent results overall.

Table A3 presents the outcomes for the firm-level analysis, specification PSM-DiD. Across each of the examined subperiods, the results remain qualitatively unchanged (and quantitatively similar) in comparison to those observed across the complete observation period (last row of the table). The positive and significant impact of FNAs on productivity thus persists after excluding the crisis years.

Table A4 presents the outcomes of the analysis conducted at the worker level, specification Job-match FE on the PSM sample. Across each of the analysed subperiods, the findings remain qualitatively consistent (and quantitatively comparable) with those observed throughout the entire observation period (last row of the table). The negative and significant, albeit small, impact of FNAs on wages thus persists after excluding the crisis years.

A.5.2 Interaction fixed effects

We conducted robustness checks to incorporate a wider set of fixed effects in the firm-level regressions. Specifically, we explored augmenting the preferred specification PSM-DiD with (i) year–size, year–industry and year–province interactions, and (ii) a full interaction term to simultaneously control for year, size, industry (defined at the two-digit level) and region.

TABLE A3 Effects of FNAs on firm productivity—specification PSM-DiD, different subperiods.

Subperiod	TFP	Labour productivity (log)	Observations
2015–18	+0.015**	+0.014**	82,979
	(0.006)	(0.006)	
2013–18	+0.013**	+0.014**	122,600
	(0.006)	(0.006)	
2012–18	+0.012**	+0.013**	142,184
	(0.005)	(0.005)	
2010–18	+0.018***	+0.021***	181,190
	(0.005)	(0.005)	
2008–18	+0.022***	+0.028***	219,383
	(0.006)	(0.006)	

Notes: Firm-level data. Standard errors (in parentheses) are clustered at the firm level. Specification PSM-DiD is described in Table 6.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

TABLE A4 Effects of FNAs on wages—specification Job-match FE, PSM sample, different subperiods.

Subperiod	$Wage_{jit}$	Observations
2015–18	−0.25%***	2,918,293
	(0.001)	
2013–18	−0.44%***	4,206,119
	(0.001)	
2012–18	−0.47%***	4,833,602
	(0.001)	
2010–18	−0.32%***	6,062,959
	(0.001)	
2008–18	−0.32%***	7,245,911
	(0.001)	

Notes: Worker-level data. Standard errors (in parentheses) are clustered at the worker level. Specification Job-match FE is described in Table 7. These estimations are based on the PSM sample.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

Table A5 displays the results for our preferred specification PSM-DiD with these two sets of interaction terms. As depicted in the table, both augmented versions, represented by rows 2 and 3, maintain qualitative consistency and are quantitatively similar to the reference specification (row 1).

A.5.3 Different thresholds for the block random sample

We carried out robustness checks to assess the sensitivity of our worker-level results to different threshold levels for the block random sampling, which is used to construct the worker-level full sample. Specifically, we explored threshold levels 15%, 25% and 30%, whereas the reference specification utilizes a 20% threshold (see Subsection 3.2, with note 6).

Table A6 presents the results of these tests. To maintain simplicity, the table reports the estimations for the preferred specification Job-match FE. Irrespective of the threshold examined,

TABLE A5 Effects of FNAs on firm performance—specification PSM-DiD, different sets of fixed effects.

Row	Fixed effects	TFP	Labour productivity (log)	Profitability
1	Year, size, industry, province	+0.022*** (0.006)	+0.028*** (0.006)	+0.039*** (0.014)
2	Year, size, industry, province, year ∗ size, year ∗ industry, year ∗ province	+0.021*** (0.006)	+0.027*** (0.006)	+0.047*** (0.014)
3	Year, size, industry, province, year ∗ size ∗ industry-2d ∗ region	+0.022*** (0.006)	+0.029*** (0.006)	+0.046*** (0.016)
Observations		219,383	219,383	204,516

Notes: Firm-level data. Standard errors (in parentheses) are clustered at the firm level. Specification PSM-DiD includes controls for a vertical integration index, firm age, employees (log), workers' shares by gender, origin, age, job contract type, job contract duration and job contract working time, and firm fixed effects. The first version (row 1) is the one reported in Table 6 and includes fixed effects for size (five classes), industry (three-digit ATECO 2007 classification), province and year. The second version (row 2) adds to row 1 year–size, year–industry, and year–province interactions. The third version (row 3) adds to row 1 a full interaction term to simultaneously control for year, size, industry (defined at the two-digit level) and region.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

TABLE A6 Effects of FNAs on wages—specification Job-match FE, full sample, different threshold levels for the block random sample.

Threshold level	$Wage_{jit}$	Observations
15%	−0.30%** (0.001)	6,310,295
20%	−0.47%*** (0.001)	8,411,953
25%	−0.42%*** (0.001)	10,503,719
30%	−0.34%*** (0.001)	12,602,223

Notes: Worker-level data. Standard errors (in parentheses) are clustered at the worker level. Specification Job-match FE is described in Table 7.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

the findings remain substantially unchanged. Consequently, the negative and significant, albeit small, impact of FNAs on wages is reaffirmed.

A.5.4 Alternative PSM procedure: controlling for pre-trends in the outcome variables

We then conducted robustness checks to assess the sensitivity of our findings to a variation in the PSM procedure, which determines the identification of the PSM sample. This alternative PSM encompasses more explicitly, among the variables used to identify the control firms, the pre-trends in the main outcome variables, that is, productivity and wages. In particular, we modified the original set of variables used in the PSM procedure discussed in Subsection 4.1 as follows. We substituted the logarithm of revenues per employee, which is a measure of labour productivity, with TFP, our primary productivity indicator. Moreover, we added the average wage of the firm, computed as the ratio between total labour costs and the number of employees. As in the original PSM procedure, for each treated firm, we select as control firms the 10 closest firms based on this updated set of firm- and workforce-level variables. The PSM sample originated by this alternative

TABLE A7 Effects of FNAs on firm performance—specification PSM-DiD, alternative PSM procedure.

Row	PSM version	TFP	Labour productivity (log)	Profitability
1	Original PSM	+0.022***	+0.028***	+0.039***
		(0.006)	(0.006)	(0.014)
	Observations	219,383	219,383	204,516
2	Alternative PSM	+0.024***	+0.028***	+0.040***
		(0.006)	(0.006)	(0.014)
	Observations	220,027	220,027	205,116

Notes: Firm-level data. Standard errors (in parentheses) are clustered at the firm level. Specification PSM-DiD is described in Table 6. Row 1 is the one reported in Table 6, where the identification of the PSM sample is based on the PSM procedure discussed in Subsubsection 4.1.1. Row 2 reports the results based on a different version of PSM, identifying a different PSM sample. In this PSM procedure, the logarithm of revenues per employee is substituted with TFP, and the average wage of the firm, computed as the ratio between total labour costs and the number of employees expressed in FTEs, is included among the variables of the PSM procedure. ***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

procedure has a total of 220,027 firm–year observations, as opposed to the original PSM sample, made up of 219,383 observations.

We then ran robustness checks to experiment with the sensitivity of our results to this different version of PSM. Table A7 reports the results for the firm-level analysis, specification PSM-DiD, based on this alternative PSM (row 2). For ease of reading, the table also reports the results based on the PSM procedure used in the paper (row 1). As can be seen, the results are qualitatively unchanged, and quantitatively very similar, in the two PSM procedures.

A.5.5 Double-PSM procedure

As a robustness check, we implemented a double-PSM procedure, at both the firm and worker levels.

The first PSM procedure, conducted at the firm level, is the one described in Subsubsection 4.1.1. This procedure identifies a PSM sample composed of 219,383 firm–year observations, including treated and control firms. The worker-level version of such a PSM sample has a total of 7,245,911 worker–year observations, constituting the workers employed in the treated and control firms. This worker-level PSM sample is the one on which we base our worker-level analysis. However, as a robustness test, we carried out a second PSM procedure at the worker level, starting from this latter sample. As for the firm level, we considered observations before the introduction of FNAs by law (i.e. referring to years 2008 and 2009). We then modelled the probability of these workers being employed in a firm that joined an FNA with the following variables: the worker's daily wage (log), gender, migration status, a cubic polynomial in age, job contract type, job contract duration and job contract working time, and dummies for firm size, sector (at the three-digit ATECO 2007 classification) and province. For each treated worker (i.e. a worker employed in a firm that joined an FNA), we selected as control workers the 10 closest (using Mahalanobis distance) workers based on the aforementioned worker-level (and firm-level) variables. The so-obtained PSM sample, which we refer to as a 'double-PSM sample', has a total of 4,666,513 worker–year observations.

On this double-PSM worker-level sample, we re-ran our worker-level analysis. In particular, Table A8 reports the findings relative to the main worker-level analysis run on the double-PSM sample (column (2)). For ease of reading, the table also reports the corresponding results on the original PSM sample (column (1)). The results are qualitatively preserved, with a minus sign that is maintained in all the specifications, from the most basic specification Raw to the most robust specification Job-match FE. Notably, there is a difference in the magnitude of coefficients in the

TABLE A8 Effects of FNAs on wages—original PSM sample and double-PSM sample.

	Original PSM sample (1)	Double-PSM sample (2)
Raw	−1.12%***	−3.85%***
	(0.001)	(0.001)
OLS1	−3.93%***	−8.20%***
	(0.001)	(0.001)
OLS2	−3.52%***	−6.50%***
	(0.001)	(0.001)
OLS3	−2.36%***	−4.56%***
	(0.001)	(0.001)
Firm FE	−0.21%***	−2.60%***
	(0.001)	(0.001)
Worker FE	−0.50%***	−0.40%***
	(0.001)	(0.001)
Job-match FE	−0.32%***	−0.26%***
	(0.001)	(0.001)
Observations	7,245,911	4,666,513

Notes: Dependent variable: $Wage_{jit}$. Worker-level data. Standard errors (in parentheses) are clustered at the worker level. The various specifications are described in Table 7. Column (1) refers to estimations conducted on the worker-level PSM sample used in the paper. Column (2) refers to estimations conducted on the worker-level sample as obtained from the double-PSM procedure, at the firm and worker levels described in Subsubsection A.5.5.
***, **, * indicate 1%, 5%, 10% significance levels, respectively.
Source: INPS-Cerved-InfoCamere dataset (years 2008–18).

two PSM samples, with larger coefficients emerging from the double-PSM sample. However, once worker fixed effects are taken into account (i.e. specifications Worker FE and Job-match FE), the coefficients in the two samples become substantially identical. In the most robust specification, Job-match FE, the impact on wages is predicted to be −0.32% in the original PSM sample, and −0.26% in the double-PSM sample.