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OCTOBER 2022

ISSN: 2365-9793

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ABSTRACT

Employer Cooperation, Productivity, and Wages: New Evidence from Inter-Firm Formal Network Agreements*

Using uniquely rich administrative matched employer-employee data, we investigate the impact of formal network agreements (FNAs) among firms under two perspectives. First, we assess the impact of joining a FNA on several indicators of firm performance, and total factor productivity. Second, we investigate whether and how such effects are transmitted to the workers, in terms of wage changes. On the firm-level side, we find an overall significant and economically relevant positive effect of FNAs on firm performance, which resists a large set of robustness tests. However, such a positive effect on firms does not translate into tangible benefits for the workers, on average. After estimating an array of multiple-way fixed effects wage regressions, we find a negative, though small, wage effect. Moreover, we detect a rather marked heterogeneity in the impacts on both firms and workers. The estimation of rent-sharing equations, as well as other tests that exploit unionization data, suggest that the negative effects on wages might be explained by a decrease in workers' bargaining power following the introduction of FNAs.

JEL Classification: L14, D24, J31

Keywords: Inter-firm cooperation, formal network agreements, firm performance, total factor productivity (TFP), wages, matched employer-employee data

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* We kindly acknowledge the data access provided by the VisitINPS program. We would like to thank Edoardo Di Porto and Paolo Naticchioni for their general help with INPS data usage. Thanks are also due to Ainoa Aparicio Fenoll, Christopher J. Flinn, Lorien Sabatino, and participants in various seminars and conferences. The opinions expressed by the authors are solely their own and do not necessarily represent the views of INPS.

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 general aim of such interactions is to cooperate in some way, to get some advantages that could materialize in terms of information or resource sharing, as well as doing some activities together. The economics and management literature generally agrees on the fact that networking creates positive economic returns for cooperating firms, arguing that isolation systematically leads to worse performances. Networking among firms can be an important source of competitive advantage (Dyer and Singh, 1998), can grant access to relevant knowledge and resources at lower costs (Gulati and Higgins, 2003; Zaheer and Bell, 2005), and allow to exploit scale economies without the disadvantages of increased size (Watson, 2011). In the same vein, recent theoretical contributions on production networks argue that the presence of numerous interactions among firms, typically in the form of buyer-supplier relationships, increases efficiency as well as firm performance (Bernard et al., 2019). While previous empirical studies agree on the positive effects of inter-firm networking for firms, pointing out that they are stronger for small and medium-sized firms (see Schoonjans et al., 2013; Manello et al., 2020, for a recent review), they fail to consider the other side of the coin. What are the consequences of inter-firm cooperation on the employees' perspectives?

On the one hand, networking might lead to increased mark-ups on the firm side, in line with the empirical findings of the literature, which may be partially distributed to employees through higher wages (Card et al., 2014). On the other hand, such cooperative agreements might be instruments for coordinating corporate strategies that go beyond their specific or explicit objectives, representing potential means for facilitating collusive practices and other forms of coordination (Krueger and Ashenfelter, 2022). This can be relevant also in the context of small and medium-sized firms that operate in narrow local labor markets (Naidu and Posner, 2022).

Gaining access to resources at a lower price, also through scale economies, is one of the main positive features of networking. However, if this applies to the labor input, the implications might be problematic. The growing market coordination of employers enhanced by networking, even if more limited than in the case of equity concentration, might represent a potential issue for the workers' wages from at least two points of view. First, employers might coordinate their actions to compress wages, according to the monopsony theories recently reviewed by Manning (2021). For example, a negative effect on wages is documented in the case of market consolidation through mergers and acquisitions (M&As; Prager and Schmitt, 2021; Arnold, 2021), as well as for concentrated markets (Azar et al., 2022; Marinescu et al., 2021). Second, the exchange of information within networks on the employer side might increase the reluctance of workers to explore outside options (Sokolova and Sorensen, 2021) and, consequently, might reduce their bargaining power following a mechanism similar to market consolidation (Schubert et al., 2021).

In this paper, we provide new evidence and a novel vision on the issue of inter-firm networking. We take advantage of a specific policy instrument, the formal network agreement (FNA), also called "contratto di rete". Such an agreement, introduced in Italy in 2009, allows collecting precise information on firms' involvement in formal cooperation. While it could imply a potential violation of antitrust principles, it is enshrined in the law since it mainly involves small firms, with alleged limited anti-competitive implications. We use a uniquely rich administrative matched employer-employee data set provided by the Italian Social Security System (INPS) to investigate the effects of such contracts on both firms and employees. We specifically concentrate on the entire population of private-sector incorporated firms - and their workers - over the period 2008-2018. We provide an analysis of the effect of a firm's involvement on FNAs from a double perspective by considering the firm's outcomes as well as the impact on workers' wages, an aspect that has never been explored before using matched employer-employee data.

Concerning the impact on firm performance, we first consider an array of standard indicators (labor productivity, profitability, and employment), finding a strong confirmation of networks' positive performance effects, compatible with increased mark-ups for network members. We then provide novel evidence by considering total factor productivity (TFP). In particular, we use the recent semi-parametric methods for the estimation of production functions, specifically designed to solve simultaneity problems and deliver consistent estimates of a firm's TFP (Ackerberg et al., 2015; Lee et al., 2019). Thanks to the longitudinal and matched nature of our data, our estimates control for unobserved fixed firm heterogeneity and an array of workforce as well as firm controls. Moreover, we deal with the non-random decision of a firm to enter FNAs by using propensity score matching (PSM) techniques combined with a difference-in-differences (DiD) estimator as well as an instrumental variable strategy and other approaches. Our firm-level results show that a firm involved in a FNA has a positive and significant impact on TFP even when networking is included in a one-step production function estimation that accounts for the endogeneity of FNAs.

A key innovation of our paper concerns the impact of FNAs on workers' wages. We estimate multiple-way fixed effects wage regressions, which, beyond several time-varying workers 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 exploiting the individual variation of wages through a PSM-DiD model, which compares treated firms and workers with an appropriate control group.

On average, we find that the workers do not get benefits from the employer's participation in a formal network, but rather they suffer a slight contraction in their wage as compared to workers not involved in FNAs. The above result contrasts with the positive impact on firm performance, suggesting that firms hardly transfer to workers the benefits gained from adhering to FNAs. We also estimate rent-sharing equations, finding results that corroborate such an interpretation. Finally, we find that the impact on workers is rather heterogeneous and seems strongly connected to the market power enjoyed by the firm. In particular, adverse wage effects are concentrated among workers employed in highly productive, medium-sized, and less unionized firms, all contexts characterized by a relatively low workers' bargaining power. Consistently, we find that weaker segments of the labor force (e.g., workers employed in low-skill jobs or less represented by unions) are the ones showing stronger detrimental wage effects.

The remainder of the paper is structured as follows. Section 2 provides a brief review of the 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 focuses on the empirical framework and the identification strategies. Section 5 presents relevant descriptive statistics. Section 6 presents and discusses the results. Finally, Section 7 draws the main implications of this study.

2. Literature and background

Predictions that inter-firm cooperation is beneficial for firms are based on several potential channels through which networking can sustain firm-level performances. The managerial literature argues that networking reduces transaction costs (Lin and Lin, 2016), makes resources more accessible and cheaper (Li et al., 2015), facilitates knowledge flows and technological improvements (Vanhaverbeke et al., 2009), as well as product or process innovations (Schøtt and Jensen, 2016). Earlier studies highlight that frequent interactions, common objectives, and collaboration in production or marketing contribute to creating reciprocal trust, reducing opportunistic behaviors, and facilitating operational advantages from networking, especially for small and medium-sized firms (Gulati and Higgins, 2003). In fact, the extant empirical evidence documents stronger positive effects in small businesses (Schoonjans et al., 2013), while specific results crucially depend on the definition of network, with weaker impacts for informal and lighter forms of collaborations (Park et al., 2010; Watson, 2011).

Recent papers rely on quasi-natural experiments to account for the endogenous choice of cooperating and are essentially based on original survey data collected through questionnaires. For example, Cai and Szeidl (2018) run a randomized experiment on Chinese firms, where inter-firm cooperation is defined as the participation of managers in business meetings with peers from other firms. They find positive effects on sales (+8%), profits, employment, and labor productivity (+4%). Other studies apply DiD estimators or similar techniques for identifying the effect of inter-firm network contracts from administrative firm-level data. 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. Dickson et al. (2021) use a PSM in combination with DiD estimations of different cross-sectional models. Focusing on employment growth at the firm level, they find significant positive effects from networking. Fabrizi et al. (2022) adopt an environmental perspective, and find support for general positive effects on employment through a system-GMM estimator, with stronger effects from 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.

However, the existing literature is typically based on simple performance indicators (e.g., survival, sales, profits, or employment), thus falling short of providing convincing evidence on structured and economically relevant measures of performance, such as labor and total factor productivity (TFP). These latter indicators are relevant in themselves, but also key for the expected impact on wages.[1] Our contribution is also aimed at filling this gap. Beyond simple performance indicators, such as profits and employment, we specifically focus on both labor productivity and TFP. This study thus provides a comprehensive and updated assessment of the performance impact of inter-firm networking, by using wide employer-employee data covering the population of firms and workers in Italy.

Considering the workers' side, the existing 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) or with a regional/local perspective (Powell et al., 1996). In particular, there is no previous evidence on the effect of inter-firm cooperation on employees' wages. According to the theory, two contrasting forces may be at stake. On the one hand, there could be a rent-sharing process, which would potentially push wages upward. As discussed before, the firm-level literature

[1] The only studies considering TFP are those by Kim (2015) and Manello et al. (2020). Kim (2015) first estimates TFP of manufacturing firms in South Korea according to the semi-parametric approach by Levinsohn and Petrin (2003) and then adopts a two-stage least squares (2SLS) regression approach. The author includes the participation in strategic alliances, another form of non-equity agreements, among the regressors, finding positive effects on TFP. Manello et al. (2020) estimate productivity according to a non-parametric data envelopment approach applied to a large sample of manufacturing firms and analyze technical efficiency in a second stage regression analysis. Arguing that the semi-parametric truncated regression model deals with endogeneity issues, they find significant positive effects on efficiency from networking, even after controlling for industry-level and time fixed effects.

suggests positive returns from inter-firm cooperation, for instance, in the form of higher profits, value added, and turnover. Such gains may be partially distributed to employees through higher wages if the firm-level rents are shared with employees (Card et al., 2014). On the other hand, cooperation (particularly formal agreements) might result in an increased monopsony power for network members, whereby wages would decrease. As argued by Cai and Szeidl (2018), a potential effect of inter-firm relationships (e.g., managers' meetings) is that of increasing collusive practices among firms, thus increasing their market power.

As highlighted by Sachwald (1998), formal cooperative agreements are a weaker form of concentration that is not involving an exchange of property rights. However, such non-equity alliances can have consequences potentially similar to M&A, and impact the market concentration through a coordinated firm behavior. Given the absence of literature on the effect of employer cooperation on wages, we retrieve precious indications 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 US 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 1-1.5%. Similarly, Arnold (2021) estimates the impact of M&As 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 labor market concentration, while M&As that impact local labor market concentration impose a 2% percent decline in wages relative to the control sample.

In a similar vein, an increase in employer concentration is expected to reduce wages. Azar et al. (2020) compute the Herfindahl-Hirschman index (HHI) by commuting zone and occupation type in the US, 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 labor market concentration and wages. Marinescu et al. (2021) use matched employer-employee data from France and analyze 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 labor markets, Azar et al. (2022) provide empirical evidence that an increase in labor market concentration is related to a significant drop in average wages. They identify more than 8,000 local labor markets, which, 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 is likely to arise in the case of inter-firm cooperation. While increasing communication among firms, it reduces outside options for workers. For instance, hostile job offers may be detected more easily, thereby limiting job-search possibilities for workers.

Our paper is also related to Krueger and Ashenfelter (2022), who examine the effects on workers' possibilities and wages of non-poaching clauses, a kind of uncompetitive agreement among firms. The mechanism on the workers' side is explained by Sokolova and Sorensen (2021). If employers reduce wages, workers respond by cutting their labor supply or by exploring outside options, eventually leaving the firm in the pursuit of better external alternatives. However, the presence of agreements to limit competition among firms, as well as other factors like geographic isolation or commuting costs, may induce workers to be reluctant to explore outside options, with consequent higher wage-setting power on the employer's side.

Another related strand of recent studies investigates the potential mediating role of unions in cursing the monopsony power arising out of market concentration from employer cooperation. Farber et al. (2018) 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.

Our paper contributes to the literature by providing a first quantitative analysis of the impact of firms' cooperation on wages, by 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 the relative importance of rent-sharing *versus* monopsonistic-power channels in determining the wage effect.

3. Institutional framework, data sources, and variables

3.1. Institutional framework: the "contratto di rete"

In application to the EU Small Business Act 2008, aimed at sustaining the competitiveness of small and medium-sized enterprises (SMEs) in Europe, Italian policy makers 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 program. 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, the formalization of programs, activities, and investments, as well as the specification of rights and duties for each participant. The normative background is intentionally flexible, allowing companies to specify in detail their program. The expected benefits are those typical of a larger size (i.e., scale economies, input sharing) reached by small firms which remain formally independent and maintain their organizational flexibility. While network agreements may limit competition, they are accepted by antitrust authorities for their worthy goals (stimulating technological innovations and improving competitiveness) and, since they mainly involve SMEs, for their alleged negligible 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 December 31st, 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.[2]

The INPS, CERVED, and INFOCAMERE data sets are then matched by using the firms' fiscal number as a firm identifier. We focus on the period 2008-2018, that is, starting from two years before the introduction of FNAs to the last year of observation of such agreements. The resulting data set, which we call "INPS-CERVED-INFOCAMERE", covers the population

[2]This register can be freely downloaded from https://contrattidirete.registroimprese.it/reti/.

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 the firm participates in FNAs or not. In this paper, we use both the firm-level collapsed data set and the matched employer-employee (i.e., worker-level) data set. We use the former to analyze the effect of FNAs on firm performance and the latter to investigate worker-level effects on wages.

We restrict our attention on 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).[3] We remove firms belonging to the mining industry (there are a few) 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 garbage disposal. Finally, for those workers that 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 less than four paid weeks and jobs reporting a number of paid days exceeding the theoretical maximum in a year (equal to 312 days).

Our data set consists of 2,023,088 firm-year observations and around 42 million worker-year observations. For computation reasons, the analysis on the worker-level data set is carried out on a 20% block random sample, which consists of 8,411,953 worker-year observations.[4]

3.3. Performance indicators and estimation of TFP

We estimate the impact of FNAs on four firm performance outcomes: (i) TFP, (ii) labor productivity, (iii) profitability, and (iv) employment. In this subsection, we describe how each of them is computed, with a focus on TFP.

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

[4] This random sample is obtained starting from the sample of firms. We select 20% of them and then consider the employees working in such firms in each year. We refer to these firm- and worker-level samples as the "full samples", as opposed to the PSM samples (see below).

In order to estimate TFP, we start by considering the following 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 modeled as a function of labor (L_{it}) and capital (K_{it}). A_{it} is the TFP of firm i in year t. Technically, it is that part of the output that is not explained by labor and capital inputs. 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:

$$A_{it} = f^{-1}(Y_{it}, L_{it}, K_{it}). \tag{2}$$

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. 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 ordinary least squares (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.[5] 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 control function method proposed by Ackerberg et al. (2015) (ACF, hereafter) represents a solution to simultaneity. In a nutshell, ACF propose using 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.[6] In this paper, we use a modified version of the ACF method. This version was recently developed by Lee et al. (2019) (ACF-FE, hereafter) and extends the ACF procedure to explicitly account 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

[5]Such a method would only deliver consistent estimates 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.

[6]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). CFEs are widely used in applied studies and represent the standard way of estimating firm-level production functions to date (Ackerberg et al., 2015).

effects thus ensures that firm-specific persistences in productivity levels are controlled for. Moreover, it improves the ability of the proxy variable to capture fluctuations in unobserved productivity. The ACF and ACF-FE methods are discussed in Appendix A in detail.

Output (Y_{it}) is measured with value added, whereas the labor input (L_{it}) is expressed as the number of employees in full-time equivalents (FTEs).[7] 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).[8] The demand for intermediate inputs (used in the ACF-FE method as a proxy for unobserved productivity) is measured by the intermediate input items of the profit and loss statement, which include intermediate goods and services used in the production process. Notably, 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.

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

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.

Finally, firm employment level is our fourth performance indicator. It is expressed as the logarithm of employees and serves to detect any changes in the size of companies following the introduction of FNAs.

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

[7] Unless explicitly indicated, we always consider employees in FTEs

[8] 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.

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, 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.

Although we do not observe working hours directly, we can precisely measure a worker's contractual hourly wage in each year. The hours of work stipulated in a full-time contract contain sector-, firm-, and occupation-specific components. We have controls for each of these components in both firm- and worker-level regressions. We then need information on the number of hours stipulated in each part-time contract. The INPS data provide us with this information. We know the exact proportion of hours of work stipulated in each part-time contract compared with the corresponding full-time contract, that is, a full-time position held in the same sector, firm, and occupation.[9] In sum, our regression analyses allow us to estimate how the contractual hourly wage of a worker changes when employing firm participates in FNAs.

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 one if firm i has ever entered into a network by year t, and zero 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 of one 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 one, in the year of entrance into the network, it remains to one and does not go back to zero.[10] Technically, after five years since the creation of a 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 one in all the subsequent years after the creation of the network. We expect that belonging

[9]This information was obtained from the INPS variable called "settimane utili".

[10]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 of FNA_{kt}.

to a 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, it remained very low in the first years. Considerable increases in the adoption of FNAs have 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.[11]

4. Empirical frameworks

4.1. Firm-level empirical framework: impact on performance

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

$$Performance_{it} = \alpha + \beta_p FNA_{it} + \gamma X_{it} + \delta D_{it} + \eta_i + u_{it}. \tag{3}$$

The dependent variable, $Performance_{it}$, indicates the performance of firm i in year t. It is, alternately, TFP, labor productivity, profitability, and employment, 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.

Firms' participation in FNAs is likely not random: firms decide whether to participate or not in a 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 (Cisi et al., 2020). Firms typically more performing, or which are experiencing performance boosts, may be endowed with stronger networks of (informal) relationships with their clients and/or suppliers, which may favor the creation of FNAs among them. If this is the case, one thus 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 a FNA to improve their situation. Again, if this is not controlled for, (downward) biased results are obtained. In sum, there may be a non-random selection of firms into FNAs. Moreover, the probability of engaging in business alliances, and then participating in network agreements, is

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

strongly influenced by the quality of corporate governance or by the ability of the managers (or of the owners, in the case of SMEs), as argued by Bodnaruk et al. (2013). In order to consistently estimate the impact of such agreements on firms and workers, it is thus important to consider these aspects.

We first estimate by OLS several versions of Equation (3), with increasing sets of control variables. We then pursue 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 a 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 of them, and the results are presented in Section 6.1.[12]

PSM-DiD estimation

We first select the firms that participate in a FNA during our observation period. These are the treated firms and the participation in a 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 a FNA during the entire observation window. Finally, we run a FE estimation of Equation (3) on the sample of treated and control firms, which we call "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 very similar to each other, one can consider the treatment, that is, participation in a FNA, 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

[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 A and the results are presented in Section 6.1.

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 labor 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 data set, we have a total of 7,245,911 worker-year observations.

CF 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 by Imbens (2004). Such a method aims at attenuating the selection-driven bias, by directly controlling for the predicted *ex-ante* probability of joining a 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 a 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 a 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 labor ratio; the returns on equity (ROE), defined as the gross profits over equity; the shares of females, non-native workers, temporary and

[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.

part-time job contracts, low-experienced workers (i.e., less 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 take into account the potentially higher *ex-ante* probability of joining FNAs for certain types of firms.

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 trust characterizing the local environment it is immersed in 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 on the cohesion of the local community. We identify local communities that are characterized by a dense system of social ties, connections, and personal networks (namely, where the level of social trust is high). In such contexts, we expect that firms will be more prone to cooperate, also formally, through FNAs. In practice, we construct, at the municipality-year level, the density of social cooperatives and other social- and mutual-purposes organizations (e.g., mutual entities and consortia) over the total number of economic organizations.[15]

The second component for the instrument (i.e., proxy number 2) derives from the observation of sectoral specificities in the network formation, 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 over the total number of firms in our sample for each 3-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.

[14] The predicted probabilities are time-invariant, since they derive from an estimation of the probability of joining a 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 the organizations that are allowed to create job positions.

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:

$$Wage_{jit} = \zeta + \theta_j + \eta_i + \iota_{ji} + \beta_w FNA_{jit} + \kappa C_{jit} + \nu_{jit}. \tag{4}$$

The dependent variable, $Wage_{jit}$, is the logarithm of the hourly contractual 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.[16] 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 i that are particularly relevant to firm i. The FNA_{jit} variable is our regressor of interest. As previously specified, it takes the value of one if worker j in year t is employed in a firm i that is part of a FNA. The β_w coefficient is thus our object of interest since it measures the impact of a firm's participation in a 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.[17] 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 a FNA. Relatedly, shocks to performance, which might translate into

[16] 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).

[17] We cannot explicitly account for the worker's education 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, therefore, largely accounted for by worker fixed effects (see also Connolly and Gregory, 2008).

variations in workers' wages, may influence a firm's decision to join a 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 a FNA. Similarly, performance shocks, besides potentially affecting the decision to take part in a 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 (4) on the (worker-level) PSM sample. This allows controlling for the time-variant source of selection on the firm-level side. 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 a FNA for the *same* worker in the *same* firm, thereby excluding potential reallocation effects stemming from new hires. Moreover, controlling for firm and worker fixed effects removes the match-specific fixed heterogeneity, which helps improve the ability of the estimator to control for any selection bias on the worker-level side.

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, both for the full and PSM versions.

Table 1 shows, separately for the full and PSM samples, the distribution of firm-year observations by participation in a FNA. As FNAs were introduced in 2010, FNA_{it} is equal to zero for all observations before that year. From 2010 onward, we detect an increasing participation of firms in FNAs. In 2018, our last year of observation, 4,252 out of 151,862 firms in our full sample participated in a FNA (i.e., 2.80%). On average, over the 2010-2018 period, FNA_{it} is equal to 1, thus indicating participation in a 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 a 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, "PSM-DiD estimation"). Table 2 replicates Table 1 for the worker-level data sets. When considering the full sample (20% block random sample), over the 2010-2018 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, such a percentage increases to 7.65%.

[Insert Tables 1 and 2 around here]

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., labor productivity) of around 48 thousand euros per year. Firms are typically profitable, with an average gross profit margin per employee equal to just above 15 thousand 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, 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 holds a temporary job contract, and 21.1% works on a part-time basis.

[Insert Table 3 around here]

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, labor 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, 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 prior to 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, labor productivity in the treated firms in 2009 is just below 49 thousand euros, whereas in the full sample in the same year it is around 47 thousand euros. Similarly, a 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 thus important to concentrate the analysis on the PSM sample, which allows comparing firms that are much more similar, in terms of dimension, performance indexes, as well as 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 belongs to FNAs (less than 1%, as previously discussed). In other words, focusing on the PSM sample avoids obtaining potentially diluted effects due to the scarce numerosity of treated firms in the full sample.

[Insert Table 4 around here]

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-West (24.3%). The PSM sample presents a more accentuated geographical difference, whereby firm-year observations from the Northern regions cover around two-thirds of the total observations (31.7% in the North-West and 34.5% in the North-West). 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 are referred to firms with between 5 and 9 employees, a similar fraction (34.1%) refers to companies with 10 to 19 employees, and a smaller proportion (19.1%) refers to firms with 20 to 49 employees. In total, 92.7% of the firm-year observations refer to firms with less 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 less than 50 employees decreases to 83.5%, and the most numerous categories are represented by firms with between 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.

[Insert Table 5 around here]

Finally, as for worker-level information, the average daily contractual 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. Overall impact of FNAs on firm performance

Here we show the estimation results of Equation (3), aimed at exploring the overall effects of FNA on the various measures of firm performance described in Subsection 3.3, including TFP, labor productivity, profitability, and employment. The estimates are shown in Table 6.[18]

[Insert Table 6 around here]

As outlined in Subsection 4.1, for each of the four 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 (3) 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)[19], 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

[18] The estimates of the β_ps coefficients of Equation (3) are to be interpreted as the difference in the considered performance indicator obtained from being a member of a FNA as compared with the specific control group of firms. All the subsequent firm-level results (i.e., Table 7) have the same interpretation.

[19] Such a control variable is not included in the regressions concerning employment.

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 in the first panel 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 magnitudes 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, labor productivity, profitability, as well as employment level by 2.2%, 2.8%, 5.8%, and 2.7%, 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 productivity, profitability, and size.

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 factors. Moreover, limited to TFP, we pursue one-step ACF-FE estimation, as discussed in Appendix B. Table 6 also reports these estimation results. In particular, the second panel of the table (i.e., Specification PSM-DiD) is related to the PSM-DiD estimation of Equation 3, 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 (i.e., when the full sample is considered). According to these PSM-DiD estimates, TFP and labor productivity are estimated to rise by 2.2% and 2.8%, respectively, as a result of joining FNAs. An increase by 3.9% is estimated to occur for profitability and by 4.0% for the employment level. Specification CF, in the third panel of Table 6 reports the estimates relative to the CF estimation of Equation (3). 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 (and simple FE estimation on the full sample).

The fourth panel of Table 6 reports the estimation results relative to the IV specification. This specification conducts 2SLS estimation of Equation (3), 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 relatively 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, the last panel of the table 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 only be used 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 reflect in increased productivity, both TFP and labor productivity, enhanced profitability, as well as higher employment levels. Our results confirm most of the previous findings by the literature (Manello et al., 2020; Burlina, 2020; Fabrizi et al., 2022), using a new and fine-grained matched employer-employees database but, most importantly, extend those findings to TFP and update the results from Kim (2015) using a new updated method. The detected TFP premia from formal cooperation remain consistent, even if reduced in magnitude, after the inclusion of networking among endogenous variables in the one-step approach.

6.2. Heterogeneities in the impact of FNAs on firm performance

The results up to now tell us that a firm's involvement in FNAs is associated with a substantial increase in various performance indicators. However, they only deliver estimates of

[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.

overall effects, thereby not telling us anything about possible heterogeneous impacts. To shed light on this issue, we explore whether the impact of participating in FNAs on firm performance is diversified across some dimensions that we deem relevant. We consider firms' location, size, and relative productive performance. The results of these analyses are reported in Table 7. We estimate a separate regression for each particular category (i.e., our regressions are run on split samples). We consider as dependent variables the usual four performance indicators, that is, TFP, labor productivity, profitability, and employment level. All of these estimates are obtained by applying the PSM-DiD estimation, as in the second panel of Table 6. Therefore, these estimates refer to the (various sub-samples of the) PSM sample.[21]

[Insert Table 7 around here]

The first dimension that we explore is the firms' location. The first panel of Table 7 presents separate regressions for the four Italian macro-areas: the North-West, North-East, Center, and South Italy, which comprises island regions (i.e., Sardinia and Sicily). Italy is characterized by substantial economic and infrastructural differences across its macro-regions, which allows shedding light on the influence of the external socio-economic and technical environment in shaping the impact of FNAs on firms' performance potential. The South of Italy is the most peripheral area, with lacking infrastructures and services for firms, the Center represents an intermediate situation, while the North-East and the North-West are the most developed areas, characterized by a prevalence of small and medium-large firms, respectively. As shown in the table, the effects are rather heterogeneous across the different macro-areas, even if to different degrees for the various performance indicators. As concerns TFP and labor productivity, the impacts, while always positive, are significant for the northern regions and the South of Italy, and not for the central regions. Moreover, we detect substantial effects in the South, with magnitudes in the range of 5.5% to 6.4%, for TFP and labor productivity, respectively. A positive and significant impact on profitability is only detected in the South of Italy, where it is estimated to be somewhat large in magnitude (10.9%). On the contrary, the impacts on employment appear to be more widespread across the national territory, with estimates ranging between 3.0%, in the North-East, and 5.5%, in central regions. Overall, while positive effects of FNAs manifest themselves in all geographical areas, they appear to be substantially stronger in southern regions, as argued by Cisi et al. (2020) for other performance indicators. This result appears coherent with the idea

[21] 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 the third panel of Table 6. The results are in line with those reported here, and are available upon request.

that FNAs are particularly beneficial in less developed areas, where sharing resources, information, and experience can represent a practical and cost-saving way of preventing isolation and compensating for the lack of infrastructures and other services.

The second dimension of heterogeneity that we evaluate is firm size, an aspect likely influencing the scope and purposes of FNAs. Objectives, characteristics, and - consequently - potential outcomes from participation in FNAs may diverge considerably across firm size, as well as the relevance of competition and market power issues related to firms' formal networking activities. We split firms into five size classes, from 5 to 9 employees, from 10 to 19, from 20 to 49, from 50 to 249, and 250 or more employees, and analyze the performance effects of FNAs on each of them. As shown in the second panel of Table 7, the effects on firm performance appear to be substantially diversified across firm size, too. While positive and significant effects on employment levels are detected across almost all the size classes (except for large firms), on productivity, both TFP and labor productivity, as well as profitability, they only emerge for small firms (10-49 employees for TFP and labor productivity and only the category 10-19 employees for profitability). The estimated effects on productivity for small firms are in the range of 2.0%-2.7% for TFP and 2.4%-3.5% for labor productivity, higher among firms with 10 to 19 employees than in firms with 20 to 49 employees. In short, these results highlight the presence of substantial heterogeneity across firm size, with positive effects emerging mainly on small firms, which are a crucial constituent of the Italian industrial structure.

Finally, we distinguish firms based on their productive performance, intending to isolate differentiated effects for more and less productive companies. We first classify firms according to the four quartiles of TFP. 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 most productive in comparison to the whole sample and not with reference to the PSM sub-sample. We then run our usual set estimations on the four sub-samples identifying the various productivity levels. The results of this last set of estimations are reported in the third panel of Table 7. We also detect a substantial differentiation in the effects of FNAs on firm performance based on productivity levels. Except for the effects on employment levels, which are predicted to be positive and significant, and with relatively stable magnitude, across all the TFP quartiles, other significantly positive effects are concentrated at the extremes of the distributions. We detect positive and significant effects, large in magnitude, particularly for the first TFP quartiles, that is, the least productive firms. For these companies, involvement in FNAs is predicted to increase TFP and labor productivity by as much as 4.4% and 6.4%, respectively, and profitability by an even larger amount, that is, 13.7%. Similarly, positive and significant effects are found at the other extreme of the distribution (i.e., the fourth quartile), though with lower magnitudes. Among such highly productive firms, involvement in FNAs is estimated to boost TFP and labor productivity by 2.1% and profitability by 3.8%. On the contrary, the impacts on these dimensions are either not significant or, while significant, very low in magnitude for intermediate categories (i.e., second and third quartiles). In these companies, positive impacts on productivity, either TFP or labor productivity, never exceed 1.0%, and impacts on profitability are not significant.[22] In sum, most of the positive effects of FNAs appear to be grasped by either least productive or most productive firms, while positive effects on intermediate-productivity firms seem to be limited to employment levels.

Hence, are the overall detected positive impacts homogeneous? The results discussed in this subsection allow us to answer this question. While effects on employment levels seem rather homogeneous, we discovered substantially heterogeneous impacts on other critical performance indicators, including productivity (both TFP and labor productivity) and profitability. On these fronts, the least productive firms, characterized by a small dimension, and located in the most disadvantaged areas seem to grasp the highest benefits out of FNAs.

6.3. Overall impact of FNAs on wages

Another question arises at this point: do the positive overall impacts of a firm's involvement in FNAs on firm performance 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 (4). The results are reported in Table 8.[23] As mentioned in Subsection 4.2, we start from basic specifications of the equation and then progressively add controls. In total, we perform the estimation of seven different specifications, one in each row of the table. Moreover, each regression is conducted on both the full sample (recall 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 4. 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,

[22] Similar results are obtained if firms are classified according to the quartiles of the 2009 TFP distribution, that is, prior to the FNA introduction.

[23] The estimates of the β_w coefficient of Equation (4) are to be interpreted as the difference in the wage of workers that are involved in a FNA (i.e., their employer is a member of a FNA) as compared with the specific control group of workers. All the subsequent worker-level results (i.e., Tables 9 and 10) have the same interpretation. Therefore, a negative estimate of β_w should not be conceived 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 proper interpretation of results and, particularly, considering the tendency of downward wage rigidity in the Italian labor market.

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. The fourth row of the table refers to Specification Firm FE, which in addition to Specification OLS3, controls for firm unobserved fixed heterogeneity, that is, includes firm fixed effects. The subsequent specification (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.

[Insert Table 8 around here]

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 favor 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, both at the worker and firm level, 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 (Specification Firm FE) or worker (Specification Worker FE) level, 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 only exploit the within-firm *and* within-worker variation 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 the attention to the PSM sample. In this case, thanks to the PSM procedure, we compare firms that are similar under plenty of 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 issues. Prager and Schmitt (2021) reported slowdown in wages between 1-1.5% for skilled workers from hospital mergers, Arnold (2021) a contraction of 2% percent only for relevant M&A in US, while Marinescu et al. (2021) find decrease around 0.5% for new hires linked to concentration increases in France.

Coming to our initial question, that is, whether the detected overall positive impacts do translate into higher wages for the workers, we can now say that the answer appears to be a "no". 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. We should nonetheless highlight that the estimated impacts of FNAs on workers' wages, while negative, are substantially modest. However, the fact remains that the positive performance effects of FNAs do not translate into higher wages for the workers. We provide more evidence on this result with rent-sharing equations in Subsection 6.5. Instead, in the following subsection, we explore whether this detected overall negative, yet small, wage gap is homogeneous in the labor market or not. We also explore whether lowered bargaining power of workers as a result of FNAs might be an explanation behind this finding.

6.4. Heterogeneities in the impact of FNAs on wages, unionization, and workers' bargaining power

The results of the heterogeneity analyses on workers are presented in Tables 9 and 10.

In Table 9, we first explore whether the effect of FNAs on wages is differentiated across job contract type (first panel in the table). 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. We then evaluate the presence of heterogeneities across workers in different firms, based on the firms' location, size, and TFP quartile (last three panels of the table). These three subdivisions retrace the categories explored in our firm-level analysis (see Table 7). Also in this case we proceed by estimating the effects in the split samples, that is, we conduct separate estimations for each category of workers analyzed. All of the estimations presented in the table account for worker, firm, and job-match fixed effects, as well as time-varying worker- and firm-level controls, as in Specification Job-match FE of Table 8. Furthermore, we concentrate on the (split samples of the) PSM sample.

[Insert Table 9 around here]

The results show that the overall negative effect on wages is not homogeneous, but that negative effects are concentrated on specific categories of workers and firms, while hiding positive and significant impacts on others. From the first panel of the table, we can see that the negative effects concentrate on low-skilled workers. For high-skilled workers, the impact of FNAs on wages, while negative, is not significant. The results in the last three panels of Table 9, which consider the characteristics of the firms in which the workers are employed, present a somewhat varied picture, with the opposition of contrasting results, significantly negative for some categories of workers and significantly positive for others.

Looking at the macro-area, we can see that the effects are polarized. Workers employed in firms located in the North of Italy, both North-West and North-East, display significant negative effects, with a relatively large magnitude (-0.99% and -0.59% in the North-West and North-East, respectively). The effects are opposite in the Center and the South of Italy. Particularly, workers employed in the southern regions are estimated to experience a significant and relatively large positive effect on wages from their firms' involvement in FNAs. While we detected positive effects on productivity, both TFP and labor productivity, for firms in the northern regions (see the first panel of Table 7), these estimates point to negative effects on the workers of such firms, thereby retracing the overall finding of positive effects for firms that are not transferred to the workers in the form of wage increases. Interestingly, we detect an opposite tendency in the South of Italy. In those regions, in correspondence of benefits for the firms from FNAs in terms of higher performance, significant positive impacts on workers' wages are detected. 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 (e.g., higher benefits on productivity and positive and significant effects also on profitability) as compared with firms located in northern regions, where the effects on performance are typically less intense.

After the firms' location, we consider their subdivision by size. We consider the same five size classes as in our firm-level heterogeneity analysis, that is, firms employing between 5 and 9 workers, between 10 and 19, 20 and 49, 50 and 249, and more than 250 workers. Again, we detect substantial heterogeneities in the impact of FNAs on wages, with impacts ranging from significantly negative to positive. Micro firms, with less than 9 employees, are associated with a not significant effect of FNAs on wages, 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), we instead detect positive impacts on wages, particularly for the first category (+0.53%). Such categories of firms are detected to experience the highest benefits in terms of firm performance, particularly productivity. Instead, the overall negative impact seems to be driven by medium-sized businesses, with 50 to 249 employees, whose workers are estimated to suffer a -0.66% effect on their wages stemming from their firm's involvement in FNAs. This category collects the highest number of workers, amounting to around 43% in the PSM sample. Notably, medium-sized businesses are found to experience no particular gains in terms of performance (we only detect a significantly positive effect on the employment level). Finally, for large firms, with more than 250 employees, we detect a significantly positive effect, which is relatively large in magnitude (+1.51%). This effect on large firms' workers comes along with a substantial no effect on the performance of such firms, as shown in Table 7.

Finally, Table 9 considers the subdivisions across the firms' TFP quartile, which are derived as explained in Subsection 6.2. Here, we can see polarized effects of FNAs on wages, with a significant positive impact for low-productivity firms (first quartile) and, on the contrary, a significant negative impact for highly productive ones, with no effects on workers in firms with intermediate productivity levels (second and third quartiles). Interestingly, both first- and fourth-quartile firms are estimated to obtain significant performance benefits, but they seem to convey these to workers in opposite ways. More in detail, workers in the first-quartile firms are estimated to benefit from a +1.78% impact on their wages following their firm entry into FNAs, whereas those in highly productive companies suffer a negative effect of -0.57%.

These results might tell us about effects that depend on the bargaining power of firms and workers and how it might change after a firm participates in FNAs. We better explore this issue in Table 10, where we try to provide evidence on the presence of heterogeneities in contexts differentiated with respect to the relative bargaining power of workers. The idea is that we should observe higher negative effects on workers in contexts where the workers' bargaining power is lower. In such a context, the potential for FNAs of acting as instruments of monopsonistic behavior for firms increases, and firms should be more able to retain the benefits of FNAs without transferring them to workers in the form of wage increases.

[Insert Table 10 around here]

Previous studies by Farber et al. (2018) and Benmelech et al. (2022) suggest that one possible limit to the expansion of employers' power is the presence of unions and the density of their membership. We perform two types of tests. One exploits observational unionization data (first panel of the table) and the other looks at the relative average wage of workers (second panel of the table), as proxies for workers', as well as unions', relative bargaining power. As for the former dimension, related to unionization, we proceed as follows. We exploit information from the 2010 RIL survey ("Rilevazione Longitudinale su Imprese e Lavoro") developed by the National Institute for Public Policy Analysis (INAPP). It is a large firm-level survey on a representative sample of Italian companies, encompassing, among the other, information on the unionization rate of each firm (i.e., the percentage of employees in the firm who trade union members). From the RIL data set, we compute the industry-level (at the two-digit ATECO 2007 level) average unionization rate, as the industry-level average share of workers belonging to a trade union over the total number of workers. We then classify the firms in our PSM sample (also this heterogeneity analysis is pursued on PSM samples) according to their unionization rate level. We thus define highly unionized firms to be those operating in industries characterized by above-average unionization rates, whereas low unionized firms are those with below-average values. Finally, we run our usual estimation on the worker-level split samples, that is, on the sample of workers in highly unionized firms and the sample of workers in low unionized firms (again, we use Specification Job-match FE of Table 9). Concerning the second dimension, related to the relative average wage of workers, we proceed as follows. We first construct (year-specific) average wages at the level of province, one for each sectoral collective contract ("contratto collettivo nazionale del lavoro" - CCNL) and job contract type (e.g., blue-collar workers, white-collar workers, middle managers). For each year and province, we thus construct the average wage of each CCNL contract and job contract type (e.g., blue-collar metalworkers, white-collar metalworkers, and so on). We then compare these provincial-level average wages with the corresponding features defined at the firm level. In other words, we construct, for each year and firm the average wage of each CCNL contract and job contract type.[24] In the case such firm-specific average wages are above province-level ones, workers are classified in the "high relative wage" category, whereas the opposite holds for the "low relative wage" category. After constructing these two classes, we run the usual estimations on each of them. We consider the former category, encompassing workers with relatively high wages, as the one where they have relatively high bargaining power, whereas the opposite applies to the latter class.

By looking at the table, we can see that for workers in low unionized firms and with relatively low wages the impact on FNAs is more negative. As concerns unionization, the impact on the workers of low unionized firms is -0.36%, around 56% higher in absolute terms than the impact on workers in highly unionized companies (-0.23%). The result we find is coherent with the work by Benmelech et al. (2022) reporting higher wage slow-downs in contexts with a lower unionization rate. The difference is even more marked when

[24] Typically, a given CCNL contract applies to all of a firm's employees.

considering the relative average wage. Workers with relatively high wages are estimated to experience a substantial no effect on their wages following their firm's joining of FNAs. On the contrary, workers with relatively low wages experience a significant negative effect equal to -0.42%. 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.

6.5. Evidence from rent-sharing equations

The last evidence we provide on the overall observed tendency by which firms experience positive performance effects that are typically not translated to their workers comes from rent-sharing equations. In practice, we estimate the following regression:

$$Wage_{jit} = \zeta + \theta_j + \eta_i + \iota_{ji} + \beta_{w1} FNA_{jit} + \beta_{w2} \hat{\xi}_{jit} + \beta_{w3} FNA_{jit} \times \hat{\xi}_{jit} + \kappa C_{jit} + \nu_{jit}, \quad (5)$$

where all the variables are the same as in Equation (4), 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 firm i's productivity level in year t, which we obtain from our ACF-FE estimation of TFP (see Subsection 3.3 and Appendix A for details). 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, this shock is unexpected and unpredictable by the firm (see Appendix A, Equation (A.9)), which 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 recent overview provided by Card et al. (2018) on this issue 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 sub-groups 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 here. It tells us of any rent-sharing effect specifically associated with the firm's involvement in FNAs. In other words, it tells us how much of the productivity gains accompanying FNAs are passed to workers through higher wages. Finally, β_{w1}, the coefficient associated with FNA_{jit}, tells us the direct effect of FNAs on workers' wages (i.e., what we estimated in Tables 8 and 9).

Our rent-sharing estimations are based on Specification Job-match FE of Table 8, thereby accounting for worker, firm, and job-match fixed effects, together with the usual set of time-varying worker- and firm-level controls. We also include, among controls, the capital to labor ratio, defined as the natural logarithm of capital over employees (both defined as in Subsection 3.3). We estimate such a rent-sharing equation on the PSM sample of workers, as usual. We first consider the overall PSM sample, and we then run the estimations on the split samples based on the categories in Table 10, that is, by unionization rate and relative average wage. The results of these estimations are reported in Table 11.

[Insert Table 11 around here]

Looking at the first column of the table, 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 8). 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 a magnitude of -0.71%. Positive productivity effects accompanying a firm's involvement in FNAs are thus not transferred to workers. Not only, the negative coefficient indicates such productivity effects within FNAs even 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. If we look at the other columns, in which we consider the different contexts in terms of the workers' relative bargaining power, we can see that such a rent-appropriating effect manifests itself with greater intensity in contexts where workers' relative bargaining power is lower, that is, when the unionization rate is typically low and so is the workers' relative wage. For instance, while negative, the estimated β_{w3} is not significant in contexts with a high unionization rate. On the contrary, in contexts characterized by a low unionization rate, it is significantly negative and high in magnitude (-1.09%).[25]

All in all, this evidence on rent-sharing estimations corroborates the interpretation of FNAs as instruments that, while benefiting firm performance, typically do not translate into higher workers' wages. This thus poses the question of FNAs as possible instruments for enhancing firms' monopsonistic positions and their bargaining power to the detriment

[25] 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.

of workers. However, it is important to stress that we focus our attention on wages, not considering other outcomes on the workers' side, such as the potential positive reallocative effects or career progressions stemming from FNAs. We nonetheless have evidence of a positive (firm-level) employment effect from FNAs, virtually across the board (see Subsection 6.2), also confirmed by other recent research on the issue (Fabrizi et al., 2022). Establishing a more global effect of FNAs on workers deserves other efforts, which should be pursued in future research.

7. Conclusions

By exploiting wide administrative matched employer-employee panel data, this paper provides novel evidence on the impact of inter-firm cooperation on both the firms' and workers' sides. We concentrate on an innovative policy instrument introduced in 2009 in Italy, the formal network agreement, which allows involved firms to co-produce, co-market, co-purchase, or co-operate in product or market development through specific contractual agreements. Such kinds of contracts, in line with the classical definition of inter-firm networks, have been introduced by policy makers with the main aim of improving the competitiveness of small businesses.

Our contributions to the literature are several. We provide novel evidence on the impacts of formal networks on firms. The firm-level analysis gives evidence on the entire population of private-sector incorporated companies in Italy over more than a decade and controls for the main sources of endogeneity, thereby providing a first large-scale and robust assessment of the impact of networks on firms. We focus on multiple performance indicators, including labor and total factor productivity. We tackle potential concerns related to the strategic decision of entering networks by adopting a DiD estimator combined with PSM techniques, together with a range of other alternative approaches (e.g., IV and one-step control function estimations). Our results are in line with previous empirical evidence of positive returns from inter-firm cooperation for firms. Overall, we find positive and economically relevant effects on both labor and total factor productivity, as well as profits. Moreover, we find that the impacts are characterized by substantial heterogeneities, whereby the network contract seems coherent with the original policy goal. Indeed, we find stronger performance gains for smaller firms, located in more disadvantaged areas, characterized by a lower productive performance.

From the worker-level perspective, as far as we know, our paper is the first that explores the impacts of employers' cooperation on workers' wages. By estimating DiD wage regressions, coupled with PSM techniques, we find compelling evidence that, during our sample period, the benefits observed at the firm level are not shared with workers, a result that is consistent with the evidence obtained from rent-sharing regressions. On the contrary, formal networking among employers seems to slightly compress the wages of their employees. However, our results indicate that the wage effects vary substantially by firm type, in a way that appears coherent with the main goals of the policy instrument, and with theoretical predictions. In contrast with the overall effect, we observe positive, though limited, impacts on wages for small firms, which are less productive and located in less developed areas. In these contexts, in which performance advantages are also stronger, we thus detect a partial transfer of benefits to workers. On the contrary, negative wage effects emerge when firms are more competitive and their bargaining power is higher, that is, among bigger firms, located in richer areas, and highly productive. 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 thus rises intriguing questions that formal networks among firms may enhance their monopsonistic power, without introducing mechanisms to compensate workers for their losses in terms of bargaining power and outside options. Policy makers should create the conditions for facilitating a sharing of advantages and profits between firms and workers. For example, they could consider promoting and incentivizing (e.g., by tax breaks) decentralized bargaining at the network level as one of the pillars of formal inter-firm cooperation, thus facilitating rent-sharing dynamics. In a similar vein, stimulating unionization within networking firms might be another way to compensate workers for the potential loss of their bargaining power.

Table 1: Firms' participation in FNAs, full sample and PSM sample

	Full sample		PSM sample	
Year	$FNA_{it} = 0$	$FNA_{it} = 1$	$FNA_{it} = 0$	$FNA_{it} = 1$
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	1,715	18,743	983
2014	184,308	2,312	18,447	1,448
2015	187,678	2,802	18,203	1,926
2016	185,863	3,284	17,945	2,512
2017	165,261	3,783	17,544	3,440
2018	147,610	4,252	17,157	4,252
Total	2,003,721	19,367	204,191	15,192

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)
Firm-level data. The PSM sample is restricted to firms that are observed in 2018.

Table 2: Workers' participation in FNAs, full sample and PSM sample

	Full sample		PSM sample	
Year	$FNA_{jit} = 0$	$FNA_{jit} = 1$	$FNA_{jit} = 0$	$FNA_{jit} = 1$
2008	721,614	0	581,506	0
2009	793,229	0	601,446	0
2010	795,172	170	608,212	489
2011	792,976	2,106	614,542	6,114
2012	771,188	5,432	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

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)
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.

Table 3: Descriptive statistics of firms, full sample

Variable	Mean	Std. dev.	25th pct.le	Median	75th pct.le
Employees (FTEs)	18.328	25.534	6.596	10.596	19
Employees (log)	2.496	0.812	1.886	2.360	2.944
Revenues (1,000 euros)	3,313.353	4,929.149	735	1,527	3,569
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
Labor productivity (value added over employees; 1,000 euros)	48.223	36.067	29.153	41.174	57.030
Labor 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
Observations: 2,023,088					

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)
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.

Table 4: Observable characteristics of firms by treatment status, PSM sample

Variable	Control firms Mean	Treated firms Mean	Std. diff.
Employees	28.211	29.280	0.035
Revenues	4,552.474	4,101.939	0.101
ROS	0.092	0.089	0.027
TFP	3.962	3.968	0.012
Labor 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
Observations: 19,495			

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)
Firm-level data. We report values for 2009, the year before the introduction of FNAs. Std. diff. reports the standardized difference between the control and treated firms (in absolute values).

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%
Center	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

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)
The full sample of workers is defined as in Table 2.

Table 6: Effects of FNAs on firm performance, full sample and PSM sample

	Dependent variable			
	(1) TFP	(2) Labor productivity (log)	(3) Profitability (log)	(4) Employees (log)
OLS1	+0.059***	+0.072***	+0.129***	+0.050***
	(0.006)	(0.007)	(0.014)	(0.003)
OLS2	+0.028***	+0.042***	+0.071***	+0.038***
	(0.006)	(0.006)	(0.013)	(0.003)
FE	+0.022***	+0.028***	+0.058***	+0.027***
	(0.004)	(0.004)	(0.011)	(0.003)
Observations	2,023,088	2,023,088	1,773,205	2,023,088
PSM-DiD	+0.022***	+0.028***	+0.039***	+0.040***
	(0.006)	(0.006)	(0.014)	(0.005)
Observations	219,383	219,383	204,516	219,383
CF	+0.020***	+0.026***	+0.044***	+0.029***
	(0.005)	(0.005)	(0.013)	(0.004)
Observations	1,140,024	1,140,024	1,007,548	1,140,024
IV	+0.038*	+0.092***	+0.197***	+0.101***
	(0.021)	(0.020)	(0.048)	(0.015)
Observations	2,023,088	2,023,088	1,773,205	2,023,088
One-step ACF-FE	+0.013**	-	-	-
	(0.005)			
Observations	2,023,088			

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)

Firm-level data. ***, **, and * indicate the 1%, 5%, and 10% significance levels. 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 of 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, among the set of endogenous variables. Employees (log) is never included in the set of controls in Column (4).

Table 7: Heterogeneities in the effects of FNAs on firm performance, PSM sample

	Dependent variable				
	(1) TFP	(2) Labor productivity (log)	(3) Profitability (log)	(4) Employees (log)	
Macro-area					
North-West	+0.019*	+0.025**	+0.034	+0.048***	69,561
	(0.011)	(0.011)	(0.029)	(0.009)	[64,754]
North-East	+0.015*	+0.019**	+0.014	+0.030***	75,772
	(0.009)	(0.009)	(0.024)	(0.008)	[70,800]
Center	+0.014	+0.019	+0.045	+0.055***	43,115
	(0.012)	(0.012)	(0.031)	(0.010)	[40,070]
South and Islands	+0.055***	+0.064***	+0.109***	+0.033***	30,935
	(0.015)	(0.014)	(0.034)	(0.010)	[28,892]
Size					
5-9 employees	+0.022	+0.025	−0.003	+0.027***	30,367
	(0.019)	(0.018)	(0.046)	(0.010)	[28,319]
10-19 employees	+0.027***	+0.035***	+0.054**	+0.034***	75,753
	(0.010)	(0.010)	(0.024)	(0.006)	[70,898]
20-49 employees	+0.020**	+0.024***	+0.025	+0.017***	76,991
	(0.008)	(0.008)	(0.025)	(0.007)	[71,843]
50-249 employees	+0.007	+0.012	+0.042	+0.054***	35,176
	(0.010)	(0.010)	(0.033)	(0.012)	[32,412]
250+ employees	+0.001	+0.010	−0.081	+0.009	1,096
	(0.023)	(0.025)	(0.114)	(0.049)	[1,044]
TFP quartile					
First quartile	+0.044***	+0.064***	+0.137***	+0.060***	24,345
	(0.017)	(0.017)	(0.049)	(0.014)	[17,455]
Second quartile	+0.003	+0.008**	−0.028	+0.034***	45,123
	(0.003)	(0.004)	(0.026)	(0.009)	[41,164]
Third quartile	+0.006**	+0.010***	+0.025	+0.052***	66,303
	(0.003)	(0.004)	(0.019)	(0.008)	[63,746]
Fourth quartile	+0.021***	+0.021***	+0.038**	+0.037***	83,612
	(0.007)	(0.007)	(0.019)	(0.007)	[82,151]

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)

Firm-level data. ***, **, and * indicate the 1%, 5%, and 10% significance levels. 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. The last column reports the number of observations; in square brackets, it is reported the number of observations for the estimations in Column (3).

Table 8: Effects of FNAs on wages, full sample and PSM sample

Dependent variable: $Wage_{jit}$		
	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

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)
Worker-level data. ***, **, and * indicate the 1%, 5%, and 10% significance levels. 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.

Table 9: Heterogeneities in the effects of FNAs on wages, PSM sample

Dependent variable: $Wage_{jit}$			
Job contract type			
Low-skilled	−0.37%***	(0.001)	4,629,366
High-skilled	−0.11%	(0.001)	2,616,545
Macro-area			
North-West	−0.99%***	(0.001)	2,365,144
North-East	−0.59%***	(0.001)	2,437,944
Center	+0.28%***	(0.001)	1,392,568
South and Islands	+1.34%***	(0.002)	1,050,255
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
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

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)

Worker-level data. ***, **, and * indicate the 1%, 5%, and 10% significance levels. 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 8. The last column reports the number of observations.

Table 10: Workers' bargaining power and FNAs, PSM sample

Dependent variable: $Wage_{jit}$			
Unionization rate			
High unionization rate	−0.23%***	(0.001)	3,268,467
Low unionization rate	−0.36%***	(0.001)	3,977,444
Relative average wage			
High relative average wage	−0.06%	(0.001)	2,832,961
Low relative average wage	−0.42%***	(0.001)	4,183,529

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)
Worker-level data. ***, **, and * indicate the 1%, 5%, and 10% significance levels. 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 contracts ("contratti collettivi nazionali del lavoro" - CCNL), and job contract type, and by comparing the latter to the same feature defined at the firm level. In the case this firm-level average wage is above the one 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 8. The last column reports the number of observations.

Table 11: Rent-sharing equations, PSM sample

	Dependent variable: $Wage_{jit}$				
	Overall sample	High unionization rate	Low unionization rate	High relative average wage	Low relative average wage
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

Source: INPS-CERVED-INFOCAMERE data set (years: 2008-2018)
Worker-level data. ***, **, and * indicate the 1%, 5%, and 10% significance levels. 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 labor 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 (PIM) 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 8.

Appendices

A. Estimation of TFP

We here present a discussion on our empirical framework for consistently estimating TFP in the context of ACF and ACF-FE estimations. For 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 following production function:

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k}. \tag{A.1}$$

We model the residual productivity, A_{it}, as:

$$A_{it} = exp\{\alpha + \omega_{it} + \epsilon_{it}\}, \tag{A.2}$$

where α is the average productivity of the firms; ω_{it} is the time- and firm-specific (i.e., idiosyncratic) productivity level; whereas ϵ_{it} is a transitory shock.[A.1]

In practice, the production function that we estimate is obtained by using Equation (A.2) and by taking logarithms in Equation (A.1):

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it}, \tag{A.3}$$

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., $E[\epsilon_{it}|I_{it} = 0]$).

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

$$p(\omega_{it+1}|I_{it}) = p(\omega_{it+1}|\omega_{it}), \tag{A.4}$$

which is known to the firm. Equation (A.4) expresses the concept that the productivity level evolves according to a first-order Markov process.

[A.1] 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 (A.2). 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.

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 imply that the firm knows the past and current productivity enhancements 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 labor 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 labor market rigidities in the Italian labor 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 labor, capital, and the firm's unobserved productivity level:

$$m_{it} = f(l_{it}, k_{it}, \omega_{it}) \tag{A.5}$$

Lastly, it is assumed that the function in Equation (A.5) is strictly increasing in ω_{it}. Conditional on labor and capital, the higher the unobserved productivity level is, the larger the demand for intermediate inputs.

At this point, ACF 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 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 (A.3) results in the following first-stage equation:

$$\begin{aligned} y_{it} &= \alpha + \beta_l l_{it} + \beta_k k_{it} + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \\ &= \Phi(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \end{aligned} \tag{A.6}$$

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 (A.6) produces an estimate $\tilde{\Phi}(l_{it}, k_{it}, m_{it})$ of $\Phi(l_{it}, k_{it}, m_{it})$.[A.2] 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}, $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*)$[A.3], as:

$$\tilde{\omega}_{it}(\beta_l^*, \beta_k^*) = \tilde{\Phi}(l_{it}, k_{it}, m_{it}) - \beta_l^* l_{it} - \beta_k^* k_{it}. \tag{A.7}$$

As ω_{it} is assumed to follow a first-order Markov process (i.e., $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$) and given $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*)$, it is possible to compute the implied innovations, $\tilde{\xi}_{it}(\beta_l^*, \beta_k^*)$, as the residuals of a regression of $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*)$ on $g(\tilde{\omega}_{it-1}(\beta_l^*, \beta_k^*))$. Following the standard practice, we proxy the function $g(\cdot)$ with a third-order polynomial in $\tilde{\omega}_{it-1}(\beta_l^*, \beta_k^*)$ (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:

$$\begin{aligned} \frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*) k_{it} = 0 \\ \frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*) l_{it} = 0 \end{aligned} \tag{A.8}$$

The search continues over β_l^* and β_k^* until the $\tilde{\beta}_l$ and $\tilde{\beta}_k$ that satisfy Equation (A.8) are

[A.2] Note that these are just the predicted values from the regression in Equation (A.6).
[A.3] They also include the constant term α, which eventually does not matter.

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:

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}, \eta_i] + \xi_{it}, \tag{A.9}$$

where $E[\xi_{it}|\omega_{it-1}, \eta_i] = 0$ and $E[\epsilon_{it}|\eta_i = 0]$. In particular, Lee et al. (2019) consider a version of Equation (A.9) where $E[\omega_{it}|\omega_{it-1}, \eta_i] = \eta_i + g(\omega_{it-1})$, which results in:

$$\omega_{it} = \eta_i + g(\omega_{it-1}) + \xi_{it}. \tag{A.10}$$

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 (A.6) with added firm fixed effects. In the second stage, it is possible to estimate β_l and β_k proceeding as before, but this time including η_i in the stochastic process of the unobserved productivity level, as defined in Equation (A.10), thereby recovering the implied ω_{it} as in Equation (A.7) and then the implied ξ_{it} as the residuals from a FE regression of $\tilde{\omega}_{it}$ on $g(\tilde{\omega}_{it-1})$, with $g(\cdot)$ being approximated with a third-order polynomial (Lee et al., 2019).

B. Endogeneizing 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 (A.1), except that the residual productivity, A_{it}, is now modeled as:

$$A_{it} = exp\{\alpha + \beta_p FNA_{it} + \omega_{it} + \epsilon_{it}\}.$$

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 modeled directly within the expression for TFP, and the coefficient β, our object of interest, captures the impact of a firm's participation in a FNA on TFP.[B.1] In sum, the production function that we estimate is the following:

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

where lowercase letters indicate logarithms.

All the assumptions described in Appendix A are maintained. In addition, here it is assumed that a firm's participation in a FNA in year t is decided, as for labor 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 formulas in Appendix A are thus adapted to include the FNA dummy. Together with an estimate of β_l and β_k, the ACF-FE estimation procedure also delivers an estimate of β, our object of interest, obtained from the following moment condition:[B.2]

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

[B.1]For the sake of simplicity, we omit the terms that refer to our control variables from Equation (A.2). 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; as well as 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.

[B.2]Estimation of augmented production functions with CFEs, such as ACF-FE, are a commonly and widely used way to solve endogeneity problems related to the variable of interest, such as FNA, in our case. Among the others, these studies have analyzed the productivity impact of sickness absenteeism (Grinza and Rycx, 2020), workers' flows and reallocation dynamics (Grinza, 2021), training (Konings and Vanormelingen, 2015), as well as the existence of learning-by-hiring effects (Parrotta and Pozzoli, 2012).

References

Ackerberg, D. A., Caves, K., Frazer, G., 2015. Identification Properties of Recent Production Function Estimators. Econometrica 83 (6), 2411–2451.

Allan, C., Maré, D. C., 2022. Who Benefits from Firm Success? Heterogenous Rent Sharing in New Zealand. IZA Discussion Papers IZA DP No. 15264.

Arnold, D., 2021. Mergers and Acquisitions, Local Labor Market Concentration, and Worker Outcomes, Unpublished paper, available here.

Azar, J., Marinescu, I., Steinbaum, M., 2020. Concentration in US labor markets: Evidence from online vacancy data. Labor Economics 66, 101886.

Azar, J., Marinescu, I., Steinbaum, M., 2022. Labor Market Concentration. The Journal of Human Resources 57 (S), S167–S199.

Benmelech, E., Bergman, N. K., Kim, H., 2022. Strong Employers and Weak Employees: How Does Employer Concentration Affect Wages? The Journal of Human Resources 57 (S), S200–S250.

Bernard, A. B., Moxnes, A., Saito, Y. U., 2019. Production Networks, Geography,and Firm Performance. Journal of Political Economy 127 (2), 639–688.

Bodnaruk, A., Massa, M., Simonov, A., 2013. Alliances and corporate governance. Journal of Financial Economics 107, 671–693.

Burlina, C., 2020. Networking Policy and Firm Performance. Growth and Change: A Journal of Urban and Regional Policy 51 (1), 161–179.

Cai, J., Szeidl, A., 2018. Interfirm Relationships and Business Performance. The Quarterly Journal of Economics 133 (3), 1229–1282.

Canello, J., Vitoli, F., 2022. Formal cooperation and the performance of Italian firms operating inside and outside industrial districts. Regional Studies forthcoming.

Card, D., Cardoso, A. R., Heining, J., P, K., 2018. Firms and labor market inequality: Evidence and some theory. Journal of Labor Economics 36, S13–S70.

Card, D., De La Rica, S., 2006. Firm-Level Contracting and the Structure of Wages in Spain. Industrial & Labor Relations Review 59 (4), 573–592.

Card, D., Devicienti, F., Maida, A., 2014. Rent-Sharing, Holdup, and Wages: Evidence from Matched Panel Data. The Review of Economic Studies 81 (1), 84–111.

Cisi, M., Devicienti, F., Manello, A., Vannoni, D., 2020. The Advantages of Formalizing Networks: New Evidence from Italian SMEs. Small Business Economics 54, 1183–1200.

Comi, S., Grasseni, M., Origo, F., Pagani, L., 2020. Where Women Make a Difference: Gender Quotas and Firms' Performance in Three European Countries. Industrial & Labor Relations Review 73 (3), 768–793.

Connolly, S., Gregory, M., 2008. The Part-Time Pay Penalty: Earnings Trajectories of British Women. Oxford Economic Papers 61 (Suppl. 1), i76–i97.

Dickson, M. M., Espa, G., Gabriele, R., Mazzitelli, A., 2021. Small Businesses and the Effects on the Growth of Formal Collaboration Agreements: Additional Insights and Policy Implications. Applied Economics 53 (46), 5397–5414.

Dyer, J. H., Singh, H., 1998. The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage. The Academy of Management Review 23 (4), 660–679.

Fabrizi, A., Guarini, G., Meliciani, V., 2022. Environmental networks and employment creation: Evidence from Italy. Journal of Cleaner Production 359, 132056.

Farber, H., Herbst, D., Kuziemko, I., S., N., 2018. Unions and Inequality over the Twentieth Century: New Evidence from Survey Data. Labor Economics NBER Working Paper n. 24587.

Grinza, E., 2021. Worker Flows, Reallocation Dynamics, and Firm Productivity: New Evidence from Longitudinal Matched Employer-Employee Data. Industrial and Corporate Change 30 (1), 75–108.

Grinza, E., Rycx, F., 2020. The Impact of Sickness Absenteeism on Firm Productivity: New Evidence from Belgian Matched Employer-Employee Panel Data. Industrial Relations: A Journal of Economy and Society 59 (1), 150–194.

Guiso, L., Sapienza, P., Zingales, L., 2015. Corporate Culture, Societal Culture, and Institutions. American Economic Review 105 (5), 336–339.

Gulati, R., Higgins, M. C., 2003. Which Ties Matter When? The Contingent Effects of Interorganizational Partnerships on IPO Success. Strategic Management Journal 24 (2), 127–144.

Huggins, R., 2001. Inter-Firm Network Policies and Firm Performance: Evaluating the Impact of Initiatives in the United Kingdom. Research Policy 30 (3), 443–458.

Imbens, G. W., 2004. Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review. The Review of Economics and Statistics 86 (1), 4–29.

Kim, M., 2015. The effect of strategic alliances on firm productiivty in South Korea. Applied Economics 47, 5034–5044.

Konings, J., Vanormelingen, S., 2015. The Impact of Training on Productivity and Wages: Firm-Level Evidence. The Review of Economics and Statistics 97 (2), 485–497.

Krueger, A. B., Ashenfelter, O., 2022. Theory and Evidence on Employer Collusion in the Franchise Sector. The Journal of Human Resources 57 (S), S324–S348.

Lee, Y., Stoyanov, A., Zubanov, N., 2019. Olley and Pakes-Style Production Function Estimators with Firm Fixed Effects. Oxford Bullettin of Economics and Statistics 81 (1), 79–97.

Levinsohn, J., Petrin, A., 2003. Estimating Production Functions Using Inputs to Control for Unobservables. The Review of Economic Studies 70 (2), 317–341.

Li, H., Corral de Zubielqui, G., O'Connor, A., 2015. Entrepreneurial Networking Capacity of Cluster Firms: A Social Network Perspective on How Shared Resources Enhance Firm Performance. Small Business Economics 45, 523–541.

Lin, F.-J., Lin, Y.-H., 2016. The Effect of Network Relationship on the Performance of SMEs. Journal of Business Research 69 (5), 1780–1784.

Maida, A., Weber, A., 2020. Female Leadership and Gender Gap within Firms: Evidence from an Italian Board Reform. Industrial & Labor Relations Review Online first.

Manello, A., Cisi, M., Devicienti, F., Vannoni, D., 2020. Networking: A Business for Women. Small Business Economics 55, 329–348.

Manning, A., 2021. Monopsony in Labor Markets: A Review. Industrial & Labor Relations Review 74 (1), 3–26.

Marinescu, I., Ouss, I., Pape, L.-D., 2021. Wages, Hires, and Labor Market Concentration. Journal of Economic Behavior & Organization 184 (2), 506–605.

Mundlak, Y., 1961. Empirical Production Function Free of Management Bias. Journal of Farm Economics 43 (1), 44–56.

Naidu, S., Posner, E. A., 2022. Labor Monopsony and the Limits of the Law. The Journal of Human Resources 57 (S), S284–S323.

Olley, S. G., Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica 64 (6), 1263–1297.

Park, Y., Shin, J., Kim, T., 2010. Firm Size, Age, Industrial Networking, and Growth: A Case of the Korean Manufacturing Industry. Small Business Economics 35 (2), 153–168.

Parrotta, P., Pozzoli, D., 2012. The Effect of Learning by Hiring on Productivity. The RAND Journal of Economics 43 (1), 167–185.

Powell, W. W., Koput, K. W., Smith-Doerr, L., 1996. Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology. Administrative Science Quarterly 41 (1), 116–145.

Prager, E., Schmitt, M., 2021. Employer Consolidation and Wages: Evidence from Hospitals. American Economic Review 111 (2), 397–427.

Sachwald, F., 1998. Cooperative Agreements and the Theory of the Firm: Focusing on Barriers to Change. Journal of Economic Behavior & Organization 35 (2), 203–225.

Schoonjans, B., Van Cauwenberge, P., Bauwhede, H. V., 2013. Formal Business Networking and SME Growth. Small Business Economics 41, 169–181.

Schøtt, T., Jensen, K. W., 2016. Firms' Innovation Benefiting from Networking and Institutional Support: A Global Analysis of National and Firm Effects. Research Policy 45 (6), 1233–1246.

Schubert, G., Stansbury, A., Taska, B., 2021. Employer Concentration and Outside Options, Working Paper Series, January 2021, Washington Center for Equitable Growth, available here.

Sokolova, A., Sorensen, T., 2021. Monopsony in Labor Markets: A Meta-Analysis. Industrial & Labor Relations Review 74 (1), 27–55.

Syverson, C., 2011. What Determines Productivity? Journal of Economic Literature 49 (2), 326–365.

Van Biesebroeck, J., 2007. Robustness of Productivity Estimates. The Journal of Industrial Economics 55 (3), 529–569.

Vanhaverbeke, W., Gilsing, V., Beerkens, B., Duysters, G., 2009. The Role of Alliance Network Redundancy in the Creation of Core and Non-Core Technologies. Journal of Management Studies 46 (2), 215–244.

Watson, J., 2011. Networking: Gender Differences and the Association with Firm Performance. International Small Business Journal 30 (5), 536–558.

Zaheer, A., Bell, G. G., 2005. Benefiting from Network Position: Firm Capabilities, Structural Holes, and Performance. Strategic Management Journal 26 (9), 809–825.