Developing a survey design for research into the role of norms in employer-employee relations: a feasibility study

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Abstract

Social norms play a central role in shaping labour markets and the relationship between employers and employees. In this manuscript, we explore the feasibility of establishing a new data source for Germany, the Norm & Employment Relationship Online Access Panel (NERO) to enable and foster research into the role of norms in employer-employee relations. Based on theoretical considerations and empirical analyses of existing German labour market data, we develop a sampling and survey design tailored to the requirements of such research.

Copyright statement

Author note

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1 Background and objectives

Social norms are a cornerstone for understanding and analysing societies. They shape most individual behaviour and collective phenomena, though despite their importance, their role in labour market behaviour and employment relationships has yet to be examined sufficiently. This is especially critical since employment relationships are highly relevant for allocation of valued resources and fundamental changes in society.

At the core of social norms is the expectation that others will evaluate one's own behaviour, and that this evaluation may have positive or negative consequences. In contrast to formal norms (like law), the enforcement of social norms does not rely on institutionalized mechanisms. Instead, social norms are typically enforced by the groups and networks an actor is embedded in (Horne & Mollborn 2020: 469). The incentives to adhere to the normative standards arise at least partially from sanctions imposed by others or by internalized social expectations. Although it has been emphasized that social norms are a basic mechanism for the functioning of societies (Elster 1989; Coleman 1990: Ch. 10; Cialdini et al. 1991; Posner 2000), their role especially in labour markets has long been underestimated. Especially in economics, the typical model of labour markets is based on pure market exchange with selfish agents. The exchange relationship between employees and employers is certainly based on those market principles, but these are in turn embedded in social networks and a society's social structure which are the structural basis of social norms for this exchange. For example, workers will evaluate how employers select their personnel, whether those are treated fair beyond the formal agreements of the labour contract or in case of a layoff. This evaluation is mostly based on social norms, whether on the level of teams, firms or the society.

Although there have been various innovative theoretical and empirical concepts to integrate social preferences and normative behaviour in the analysis of labour markets (Dufwenberg & Kirchsteiger 2000; Fehr et al. 1998), past research has focussed on quite general norms and principles and has documented their relevance using innovative, well-designed lab and field experiment in selected contexts. However, the research on social norms in the labour market suffers from the lack of a broader empirical data base and is fragmented into disciplinary areas. As a result, there is a gap in theoretical and empirical knowledge to what extent social norms in labour markets exist, whether they are considered important and how they affect interactions in the work environment.

Uncovering the normative basis of the exchange between employees and employers will enhance our understanding of employment relationships and the labour market in general. For example, the implementation of new technologies at the workplace may fail because social norms clash with the surveillance possibilities these technologies allow for (Abraham et al. 2019). Or more flexible labour contracts may be rejected due to normative beliefs that those contracts contravene fairness principles. These examples show that the design and the functioning of employment relationships can be influenced strongly by social norms, and without a deeper understanding of these underlying normative principles the management and governance of employment relationships may be inadequate or counterproductive.

Figure 1 summarizes some of these considerations and displays a general framework for the analysis of social norms in the labour market: Social norms emerge from economic and social structures in a society, and – depending on the norm's strength and validity – employers and employees respond to those norms according to the incentives provided by relevant other actors. These responses comprise compliance/deviance as well as attempts to change the norm or to avoid situations regulated by norms, among others.

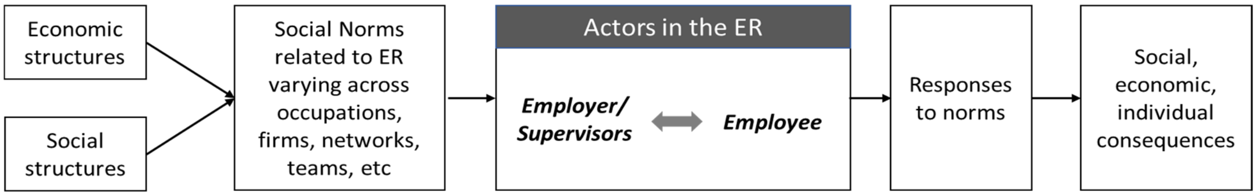

Figure 1: General framework for the analysis of social norms in the labour market

One main reason for our limited knowledge on social norms for labour market process is lack of data. While there is no shortage of data collection efforts capturing labour market relevant facts such as employment situations, salaries, educational attainment etc., the key Germany data sets in this space – such as GSOEP, PASS, NEPS, and others – include only rudimentary measurements on social norms, and rarely capture sufficient characteristics of the employment relationship. Almost entirely missing is information on the normative basis of the employment relationship. The situation is similar in other countries. Furthermore, recent research on norms demonstrated the usefulness of experimentally manipulating situational determinants or subjective beliefs to understand the behavioural effects of social norms (Bicchieri 2017, Görges & Nosenzo 2020). Existing data do not allow for such experimental investigations into social norms, especially for a wide range of topics in employment relationships. In what follows we specify features of an ideal data collection, which would allow closing the knowledge gap. Such a data collection effort ideally (a) has the power to provide results which are generalizable for the German labour market, (b) is large enough to focus on specific subsamples confronted with specific norms, (c) is flexible enough to cover different types of situations and norms, and (d) provides the opportunity to implement experimental designs on norms. Furthermore, (e) social dynamics related to social norms as well as their change over time should be covered in the data collection.

2 General survey design

From these objectives, we derive that longitudinal data are needed and that an online access panel is ideally suited to fulfil the different requirements. A panel design is not only a prerequisite for analysing individual change in the perception of norms, it also facilitates identification of causal effects, e.g. by allowing the use of fixed effects models that exclude time-constant unobserved heterogeneity (Brüderl & Ludwig 2015).

The design of the study has to be flexible enough to incorporate research questions from different topics and disciplines and with a variety of data collection methods like standardized questions, vignette studies, virtual labs or diaries.

We suggest that once recruited, all panellists answer a welcome survey with baseline information (e.g., on demographics) and are later requested to participate in semi-annual panel waves (NERO$_L$) that collect data of broad relevance for research on social norms in employment relationships, e.g., on personal normative beliefs and social expectations concerning employment relations. In addition, the access panel serves as a source for probability-based subsamples for different projects. The main advantage of this design is that stand-alone projects can draw tailored subsamples based on the information available from the two annual surveys as well as the sampling frame (for more information, see below). Thus, probability samples limited to or oversampling of specific groups (e.g., newly hired employees, employees who have witnessed layoffs in their establishments, employees who decide about recruitments, employees with childcare obligations) are easily acquired. Furthermore, project specific samples can be tailored to the required data structure – either as simple random samples or as samples of employees clustered in establishments – enabling a probability framework even for experimental studies. Last but not least, the online sampling is highly cost-effective and allows to set up a real panel study for a fraction of the cost a classical panel would require.

3 Sampling design

In order to be able to identify and describe social norms that prevail in working life, it is indispensable that the panel is based on a “representative” sample, in the sense that data are from a probability sample from a well-defined and broad target population.

At the same time, it is vital to consider the embeddedness of respondents in firms that shape their beliefs and expectations and to acquire data on employee-supervisor-dyads.

3.1 POSSIBLE SAMPLING APRROACHES

At least three different approaches to arrive at such a sample need to be discussed:

A) Sampling establishments or companies as primary (first stage) sampling unites and selecting employees within (second stage)
B) Sampling individuals as primary sampling unites, and use those as seeds for their establishments / companies in a network sampling approach
C) Sampling from a database that contains information on employees and establishments

A) Sampling establishments or companies and selecting employees within

Establishments or companies can be sampled from registers and approached with the survey request. All employees within the cooperating establishments will be selected, or a random sample of employees within the companies will be selected. The random sampling will ideally be done by the researcher (though algorithms can be provided to the companies should handing over a list of employees for sampling purposes not be feasible). Advantages of this design are that with the support of employers it is likely that within participating establishments employee response will be high. In addition, this design easily allows sampling of units within the organization. However, in this scenario, employers or their representatives act as gatekeepers who decide whether an establishment participates or not. Furthermore, research ethics require transparency on the study topic, and it is conceivable that revealing the research topic will lead to a systematic underrepresentation of establishments with internal norms that are conflicting with social norms outside or even with legal norms. Such a selection bias on one of the major outcome variables renders this option undesirable. There is no straightforward way to correct for nonresponse bias caused by what we intend to measure. Statisticians refer to such situations as not missing at random (NMAR) missingness mechanism (Rubin 1976).

B) Sampling individuals as seeds for their establishments / companies

A different approach could be based on drawing a high-quality random sample of the general population (e.g. from municipal registers) and – after screening whether the respondent is currently employed – asking the respondent to pass on the invitation to colleagues in some form of snowball (Goodman 1961) or respondent driven sampling (Heckathorn 1997). Among the merits of this approach would be that each employed person would have an equal chance to be selected as a seed irrespective of the kind of employment and of employers' attitudes towards the study. However, the indirect sampling of colleagues has obvious drawbacks related to uncertainty in the estimation of selection probabilities (Gile & Handcock 2010) and inefficiencies due to unequal selection probabilities not under control of the researcher (Goel & Salganik 2010). Furthermore, there might be the ethical issue that – if employers disapprove of their employee's taking part in the study – the initial seed might be held responsible.

C) Sampling from a database that contains information on employees and establishments

The most straightforward way to produce such a sample would certainly be to draw from a database that includes information on both, employees and establishments, as well as on which employee belongs to which establishment. Such a database allows for a combination of two stage sampling (employees in establishments) for large establishments with one stage sampling for small establishments (in which the number of employees is too small to establish a multilevel data structure) in one unified framework with easily computable selection probabilities.

There is a high-quality administrative database that contains all this information: The IAB Employee History (BeH; IAB 2020a). It is based on employers' social security notifications and thus comprises all employees subject to social insurance contributions. This database and structure entails several advantages for the planned project. The coverage of the target population is excellent, with an estimated 97 to 99 percent coverage. The sampling frame contains rich information on the employees' employment history (including wages, occupation, qualification) and can easily be linked to the Establishment History Panel (BHP, IAB 2020, Ganzer et al. 2021) which contains rich information on the establishments they work in (including industry and all aggregated employee attributes like wage distribution). These frame data allow stratifying the sample according to the need of the research projects (e.g. by supervising position or tenure; see below).

Furthermore, it allows the linkage of the survey data to the administrative data on employees and establishments for all respondents who provide informed consent. The IAB has ample experience with this kind of data linkage and usually achieves consent rates of 80-90 percent, a recent example being 84 percent in the HOPP online panel (Haas et al. 2021).

These advantages come at the cost of the database being limited to employment subject to social insurance contributions including marginal employment. According to official statistics 37.583 million out of 44.792 million employed persons in Germany fell into these categories in 2020, that is 83.9 percent of all employed (https://www.destatis.de/DE/-Themen/Arbeit/Arbeitsmarkt/Erwerbstaetigkeit/Tabellen/eckwerttabelle.html, retrieved April 28th, 2021). The major groups that are not covered are the 3.999 self-employed and the 1.703 million civil servants ("Beamte").

We argue that for the analysis of the role social norms play at the labour market, the exclusion of these groups is not critical. Since we focus on employee-employer relationships, self-employed persons without any employees are not within our focus anyway. Self-employed with employees are employers and are covered at least partially by the sampling and instruments covering the firm side. As for the civil servants, there may be in addition to general norms special ones in their relationships to their employer (the state). However, civil servants are a comparably small group (3,8% of all employed persons) with a highly stable employment relationship. Since we are interested in the role of norms for the general labour market, we argue that civil servants are a very special case which can be neglected in a first step. However, this group could be integrated later on by setting up an additional sample.

3.2 SUGGESTED SAMPLING DESIGN

Figure 2 shows the general sampling design and the resulting samples. As can be seen, we plan to draw two random samples out of all persons employed at the last available reference date. For sample A, we will use the statistically more efficient simple random sampling for all employees in establishments with less than 100 employees, because cluster sampling would result in only few interviews per establishment. For sample B, we intend to use two stage clustered sampling for employees within establishments with 100 or more employees. Establishments are sampled with probability proportional to size (Skinner 2014) and then a fixed number of employees is sampled per establishment. This design allows multilevel analyses of effects at the establishment as well as on the individual level.

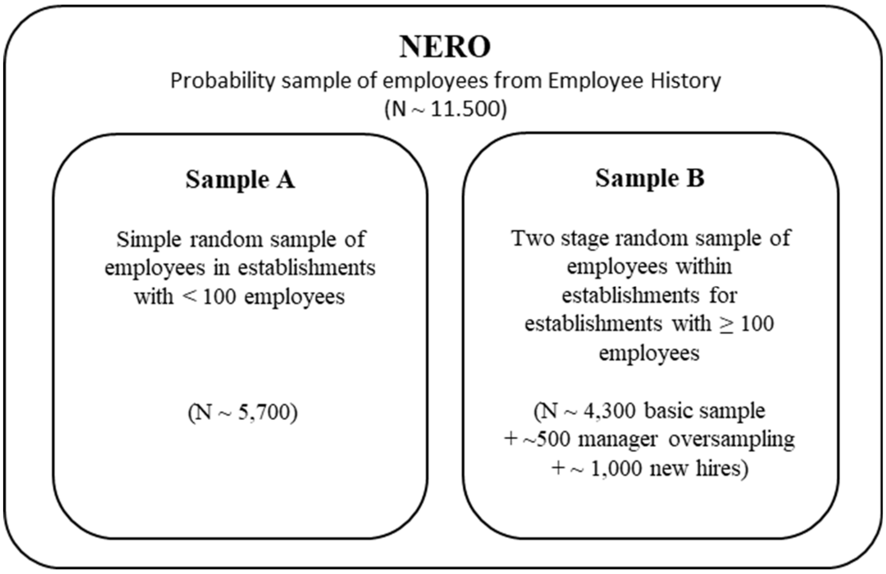

Figure 2: NERO subsamples

A test draw in December 2020 revealed that if we assign equal probability to each employee and recruit 10,000 respondents, this will result in about 5,700 employees from smaller establishments in Sample A and 4,300 employees, clustered in 215 establishments (with approx. 20 respondents each) from establishments of size 100 or more in Sample B. While the case numbers (on each of the levels) in the clustered part of the sample easily allow the application of multilevel modelling, they might not guarantee a sufficient number of supervisors per establishment for the analysis of supervisor-employee dyads. Supervisors can be identified in the sampling frame either by their occupation code or by modelling the probability that they classify themselves as a supervisor based on an analysis combining the Employee History with survey data (PASS-ADIAB). A test run in December 2020 revealed that even with the most restrictive definition about 12 percent of the employees in larger establishments are in supervisor positions. By assigning a higher selection probability to supervisors, we can thus ensure for most of the 215 establishments to recruit multiple supervisors. We expect that about 500 extra cases in Sample B will result from this supervisor oversampling.

In order to enable research on a crucial phase of getting to know local norms – the onboarding process within companies –, we will regularly top up the sample with newly hired employees of the 215 selected establishments. These are drawn from employer's notifications within three months of their hiring. Newly hired employees will be oversampled. This will lead to a maximum of 1,000 extra recruited cases in Sample B over the course of the project. Altogether this will lead to sample sizes of about 5,700 (Sample A) and 5,800 (Sample B). While response rates for online panels tend to be lower than in other – more expensive – survey modes, our survey comes with excellent possibilities for nonresponse adjustment (Groves 2006, Valliant et al. 2013): Our sampling frame includes detailed information on employment histories and establishment attributes for respondents as well as nonrespondents. From these we will derive weights to reduce any biases in variables correlated to variables in the employee history that are associated with nonresponse. A similar approach regarding sampling, recruiting, and weighting has been adopted in an online access panel from the same data source for the IAB high frequency panel survey HOPP (Haas et al. 2021) established in the context of the Covid-19 pandemic.

3.3 SAMPLE SIZE AND POWER ANALYSES

Since the overarching theme of social norms in employment relationships comprises a multitude of research questions that will need to make use of different subsamples of the access panel, a power analysis in the strict sense is not feasible at this point. Power analyses will depend on specific research goals in individual projects, especially when determining sample sizes needed for specific subsamples. Instead, we illustrate here the estimation precision for different scenarios, distinguishing between:

a) analyses in the first wave full sample of $NERO_L$ (n=10.500),
b) analyses in a later wave full sample of $NERO_L$ (n~6.250) for which we assume the loss of about half of the participants due to attrition and 1.000 extra interviews with newly hired employees,
c) analyses based on the first wave of the cluster sample NERO-B (n=4.800),
d) analyses based on a later wave of the cluster sample NERO-B, again assuming about 50 percent loss due to attrition and 1.000 extra interviews with newly hired employees (n~3,400),

The two-stage sampling design will cause a design effect (d^2) that will reduce effective sample sizes for many applications, where the effective sample size depends on intra-cluster-correlation (ICC or ρ) as well as the number of interviews per cluster (b). ICCs will differ between variables. We will assume a comparatively large ICC of .05 for the following estimations (reflecting the assumption that norms will correlate substantially within establishments) and an equal distribution of cases across the 215 establishments in the clustered part of the sample (NERO-B). We will ignore additional variance potentially introduced by unequal weights and gains in precision of estimates of change due to within respondent correlation across time. Using the approximation of the design effect as given e.g. in Groves et al. 2009 ($d^2=(1+(b-1)*\rho)$, this leads to effective sample sizes of

a) 5,700 + 4,800 / (1+(22,3-1)*0.05) = 8.024
b) 2,850 + 3.400 / (1+(15,8-1)*0.05) = 4.804
c) 4,800 / (1+(22,3-1)*0.05) =2.324
d) 3.400 / (1+(15,8-1)*0.05) = 1.954

In Table 1, these scenarios are reflected in the rows, while the columns reflect different analyses scenarios:

i) We want to test whether the proportion agreeing to a certain norm is equal to .3. How much larger (or smaller) than .3 does the population proportion have to be if we assume an alpha of .05 and a power (1-beta) of .9, i.e. to get a result significantly different from .3 at the 95-percent-level of confidence in 9 out of 10 samples?
ii) We want to test whether there is a difference between two groups concerning the agreement to the norm. Each group comprises one third of the sample. Assuming that the agreement is .6 in one group. How much larger (or smaller) does it have to be in the other group to detect a significant difference at the 95-percent-level of confidence in 9 out of 10 samples?
iii) We want to detect whether the agreement to a norm that was .5 in the first wave has changed in later waves. How much larger (or smaller) does it have to be in the other group to detect a significant difference at the 95-percent-level of confidence in 9 out of 10 samples? (only for scenario a and c).

All numbers in Table 1 were calculated using the *sampsi* command in Stata 16.1.

Table 1: Size of differences that can be identified in 9 out 10 significance tests at alpha=.05 for different scenarios

	i) one group != .3	ii) two groups .6	iii) longitudinal .5
a) 1st wave $NERO_L$	.017	.043	.030
b) later wave $NERO_L$	.022	.056	
c) 1st wave NERO-A	.032	.08	.050
d) later wave NERO-A	.034	.087	

Table shows that for most scenarios the selected sample size is sufficient to detect differences of 2 to 5 percentage points. Only in application ii) where we compare two subgroups within the sample that each comprise one third of the sample are larger differences in the population required in order to detect them in 9 out of 10 samples.

3.4 RESULTS FROM A TEST DRAW

In order to be able to take informed decisions on the survey design, we simulated a test draw based on the 2018 Establishment History Panel (BHP). The BHP contains all establishment with at least one employee and a variable denoting the number of employees. This variable gives us the distribution of employees and enables us to simulate how employees would be distributed across establishments in a simple random sample or in a two-stage sample with establishments as stage one sampled with probabilities proportional to size and a fixed number of employees per establishment. Table 2 gives the distribution of establishment sizes in a simple random sample of employees.

Table 2: Estimated distribution of establishment sizes in a simple random sample of employees

Percentile	Employees
1%	2
5%	3
10%	6
25%	17
50%	69.5
75%	327
90%	1030.5
95%	2703
99%	14473

Notes: Mean number of employees: 915.78

In a simple random sample of 10,000 employees 4,300 would be from establishments with 100 employees or more and 5,700 would be from smaller establishments.

Given that a simple random sample is statistically more efficient than a cluster sample, but that a cluster sample is required to have a sufficient number of employees per establishment to estimate within-establishment effects, we consider it optimal to combine simple random sampling for smaller establishments (less than 100 employees) with cluster sampling with probability proportional to size for larger establishments (100 employees or more).

With an estimated recruitment rate of 20 percent, we will be able to sample 20 employees from each of the larger establishments. Thus, a design that would assign equal probability to each employee could be achieved by sampling 5,700 employees from small establishments as a simple random sample and by sampling another 4,300 employees in a two-stage design from 215 establishment with 20 employees each (where establishments are sampled proportional to size).

3.5 IDENTIFYING SUPERVISORS IN THE IAB-BeH

Identifying managers in German administrative data is theoretically possible by using the information on the classification of occupations (Klassifikation der Berufe; Kldb). If the fourth digit of the KIDB code is a “9”, this indicates that the employee has managerial or supervisory duties. Furthermore, the Kldb Code “7110” indicates being an executive. Theoretically, using these should suffice to identify managers.

However, in practice, employers often do not update this information if a promotion happens. This means, for example, if an employee start working at an establishment of a given firm without supervisory duties and is promoted to a supervisor or managerial position, it could be the case that she simply keeps her original Kldb information in the administrative data as there is no incentive for employers to update this information. Therefore, employers might only update information on pay and the contract duration. Thus, we would falsely identify her as a non-manager.

As a solution, we use information from the Panel Study Labour Market and Social Security (PASS, Trappmann et al. 2019, IAB 2020c), linked with administrative records (PASS-ADIAB, Antoni & Bethmann 2014, IAB 2020d) to use survey information on supervisory duties to identify managers in administrative records. This is achieved by regressing supervisory status (which is a simple questionnaire item in the PASS on whether on has either supervisory or managerial duties over employees) on a set of variables from the administrative data and then using the coefficients from this regression to estimate the propensity of being a manager in administrative records. Specifically, we estimate the following model with a logit regression:

$$\Pr(Manager = 1)_{it} = \beta_0 + \beta_1 Kldb'_{it} + \beta_2 X'_{it}$$

X' contains daily pay (cubic polynomial), labour market experience and job tenure (squared polynomials, respectively), gender, education category dummies and age and survey year fixed effects. $Kldb'$ is a measure for the occupation in the administrative record. In our baseline specification, we use the the 3-digit-Kldb measure as well. We identify individuals as supervisors for whom the model predicts an above 80% chance to be a supervisor. In additional analyses, we also use a simple binary definition from the Kldb as well as the 4-digit-codes as alternatives.

Either prediction identifies more supervisors in the data than simply using the original occupation classification when brought to administrative records. On average, we would identify 2.3 at the mean (1923, median: 1) supervisors in establishments with less than 100 (100 and above) employees, compared to 3.7 (7932, median: 1) supervisors when using the prediction with the 3-digit classification of occupations. Thus, the procedure allows us to identify more employees with managerial or supervisory duties compared to using only information from administrative records (for more details see Collischon 2021).

3.6 SAMPLE RECRUITMENT AND SURVEY OPERATIONS

The sample will be recruited by IAB in a procedure using multiple invitations and reminders based on the total/tailored design method (Dillman 1978, Dillman et al. 2014) in order to achieve a high recruitment rate. The operation of the access panel will be delegated to a fieldwork agency experienced with administering online access panels. We will use an established incentive scheme for online access panels to boost the motivation to participate regularly.

3.7 DATA LINKAGE AND DATA ACCESS

The resulting dataset results in a register file including response patterns and demographic information for each respondent, a long file including the data from all baseline surveys (collected twice per year), a file with weights (cross sectional as well as longitudinal) and separate files for the surveys or experiments from the separate projects of the research group. The data and the data collection will be documented in a detailed data documentation report.

The resulting data set can be made available for external researchers who could submit proposals for their own data collection projects. Moreover, an anonymized dataset could be made available to all external researchers via the Research Data Center at IAB.

One large asset of the dataset is that all survey data will be linked to IAB administrative data for all respondents who give their informed consent. IAB has experience achieving consent rate of more than 80 percent in self-administered interviews (e.g. (Haas et al. 2021).

4 SUMMARY

In this manuscript, we propose the installation of an online access panel survey for research into the role of norms in employer-employee relations. The panel is intended to close a gap in the research infrastructure for research on social norms on the labour market. From the most pressing research questions in the field, we derive a survey design that tailors optimally to the diverse needs. We suggest an online access panel of about 11,500 respondents with semi-annual panel waves. Participants are sampled from an administrative database with excellent coverage that contains information on employees and employers. This guarantees sufficient numbers of employees per establishment in order to apply multilevel analysis methods. Supervisors and newly hired employees are oversampled in order to generate sufficient case numbers. Furthermore, the access panel serves as a sampling frame for projects that require specific groups of employees (e.g. newly hired, supervisors). These projects can recruit access panel members for regular surveys, dairy studies, online lab experiments or vignette studies. In this way, the suggested new data source caters to diverse research gaps in the area of norms in employment relationships and allows for a variety of methodological approaches.

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