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Abstract

Many people derive a sense of impact or purpose from their jobs – they consider work to be a source of *meaning*. But how to make work meaningful? Theoretical models suggest that meaning can be created through social and non-social impact. We exploit rich panel data to empirically assess these models, and estimate a nonlinear production function for work meaning that allows for noisy and complementary inputs. We find that social impact is the most effective pathway to meaning, and estimate a direct output elasticity of about 0.55. We also find evidence of a negative interaction with non-social impact. A standard deviation increase in social impact is twice as effective in creating meaning for individuals that perceive their jobs as having little non-social impact, compared to those with high perceived non-social impact.

Keywords: work meaning, production function, latent factor model

JEL Codes: D91, J32, D24

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1 Introduction

Many people derive a sense of impact and purpose from their job – they consider work to be a source of *meaning*. A substantial body of work that spans organizational psychology, sociology, and economics studies the importance of work meaning – see Rosso et al. (2010), Martela and Riekki (2018), and Cassar and Meier (2018) for recent reviews. This literature has found that meaningful work is related to various benefits in the workplace, such as higher productivity (Ariely et al., 2008; Chadi et al., 2017), reduced turnover (Burbano et al., 2023), fewer absences (Steger et al., 2012), and lower reservation wages (Hu and Hirsh, 2017; Kesternich et al., 2021). So how can we make work meaningful?

Theoretical work in psychology and economics identifies four pathways to meaning (Martela and Riekki, 2018; Cassar and Meier, 2018). The first pathway is beneficence, or the feeling of making a positive *social impact* through work, by helping other people or society at large. The other three pathways are derived from self-determination theory, which posits that human well-being is rooted in the satisfaction of three basic needs (Ryan and Deci, 2000). The first need is a for *autonomy*, or a sense of freedom and flexibility over work methods and arrangements. The second is for *competence*, or the perceived ability to apply one's talents, skills, and knowledge. The third is for *relatedness*, or the connection workers have with their colleagues, supervisors, and the firm. As in Burbano et al. (2023), we will also refer to these three components as creating meaning through *non-social impact*.[1]

How effective are the different pathways at creating meaning? We address this question by estimating a nonlinear, within-individual, production function. To do so, we exploit four waves of panel data from the American Working Conditions Survey (AWCS), a representative survey of workers in the United States. The longitudinal nature of this data allows us to overcome concerns related to individual-specific interpretations of the answer scales and time-constant differences in productivity or personality traits, which may determine perceptions of both work meaning and the pathways. We further use an estimation procedure recently introduced by Agostinelli

[1]When we talk about work meaning or any pathway throughout this paper, we refer to the individual's perception. Two people that work the same job may perceive different levels of social impact or meaning, depending on their idiosyncratic assessments. The production function estimates how these perceived levels translate into perceived meaning. These are interesting objects by themselves, and we expect them to correlate significantly with more objective levels.

and Wiswall (2025) to deal with measurement error. This allows us to take into account that the survey questions used to measure work meaning and the pathways are noisy, with answers that differ in locations and scales, and that vary in the information they contain about the underlying latent concepts.

The first main empirical result is that work meaning can be produced through all four pathways, in line with the theoretical model of Cassar and Meier (2018). But there is substantial heterogeneity in their effectiveness. We find the the sense of having a *social impact* has the largest direct output elasticity, at 0.54 in our preferred specification. The effects of *autonomy* and *relatedness* are smaller, with direct output elasticities between 0.125 and 0.15. The least effective pathway is *competence*, with an output elasticity of about 0.04. We show that ignoring either measurement error or individual-specific heterogeneity significantly changes the estimated parameters. Not addressing either concern leads to a significant over-estimation of the importance of non-social impact. This may explain why previous work documents widely different correlations between meaning and the pathways across sample that differ in their homogeneity – see for example Martela and Riekki (2018).

The second main result is that the different pathways interact in the creation of meaning. Particularly, we estimate a significant negative interaction between social impact and the three other pathways. This highlights that creating meaning by improving social impact through work is particularly effective for individuals who perceive their jobs as having only little non-social impact, and vice versa. While prior work such as Grant (2008) often emphasizes the synergy between intrinsic and prosocial motivation, our results suggest that increasing perceived social impact is a particularly effective way to create meaning when other motivational resources are scarce. This is relevant to increase labor supply of lower skill workers, whose jobs are more likely to lack complexity, autonomy, and skill variety, and whose labor supply has been declining steadily (Acemoglu and Autor, 2011; Autor, 2015; Binder and Bound, 2019).

To interpret the magnitude of these findings, we price work meaning in terms of the equilibrium compensating differential that people pay in the labor market. We find that a standard deviation increase in work meaning is worth around 220 dollars of monthly earnings ($\approx$ 4.7%). This is in line with recent willingness-to-pay estimates for the United States reported in Maestas et al. (2023). We find that a standard deviation increase in non-social impact is equivalent to about 70 dollars of monthly salary. On the other hand, a standard deviation increase in social impact is valued at about 118 dollars. But this value largely depends on how individuals perceive the non-social impact of their jobs. Those that consider their jobs as having little non-social impact value the increase at 156 dollars, whereas those that indicate high non-social impact value the increase at just 80 dollars.

The final step in our analysis is to study differences in social and non-social impact across occupations. This allows us to pinpoint where improvements could be the most effective. First, we find that there is a lot of occupational heterogeneity in the fraction of workers that perceives their jobs as having only little social or non-social impact. We highlight in particular that many workers in Transportation, Food Preparations and Serving, and Production report low levels of both social and non-social impact. Improving their feelings of social impact would be a particularly effective way to increase their work meaning, which we also document to be particularly low. The recent efforts that firms have spent on building extensive Corporate Social Responsibility programs and crafting intricate Mission Statements – see for example Cassar and Meier (2018) for a broader discussion – could be a step in the right direction, but more directed efforts towards particular occupations could be particularly beneficial. On the other hand, people in Health Support and Social Service occupations report high levels of social impact but low non-social impact. In these occupations, increasing non-social impact by enhancing feelings of autonomy, competence, and relatedness can be effective. This may for example be achieved through further technological progress aimed at making workers better substitutes for one-another, as shown in Goldin and Katz (2016).

Literature We contribute to the body of work that studies the importance of work meaning (Rosso et al., 2010; Cassar and Meier, 2018; Martela and Riekki, 2018; Burbano et al., 2023). The various beneficial consequences are well documented, but there is little empirical evidence about what makes work meaningful. Previous papers have studied the effectiveness of workplace interventions that change workers' meaning in the lab and in survey experiments (Ariely et al., 2008; Kesternich et al., 2021; Ashraf et al., 2024; De Schouwer et al., 2025). We highlight the usefulness of compensating differentials as a simple tool to price such interventions, and show that responses may differ substantially between occupations.

There is also evidence of cross-sectional correlations between work meaning and the different pathways highlighted in theoretical models (Martela and Riekki, 2018; Nikolova and Cnossen, 2020; Burbano et al., 2023). But the extent of these correlations differs significantly across samples, so it is unclear how strong the associations are. We introduce tools from the literature on human capital formation to estimate a within-individual production function of meaning that allows for noisy measures (Cunha and Heckman, 2007; Cunha et al., 2010; Agostinelli and Wiswall, 2025). We find that accounting for measurement error and heterogeneity across individuals is important to understand the relation between work meaning and the different pathways. We also highlight the importance complementarities, in line with theoretical predictions in Cassar and Meier (2018).

We also add to the literature on compensating differentials for amenities in the workplace (Rosen, 1986; Lavetti, 2023; Bell, 2024). We estimate a compensating differential for work meaning in the United States that is in line with other recent estimates by Burbano et al. (2023) for Sweden, and with the willingness to pay for pro social impact found in Maestas et al. (2023) and De Schouwer and Kesternich (2024). Several other papers document similar equilibrium prices for other concepts related to social impact, such as sustainability and jobs in the non-profit sector, see for example Leete (2001) and Krueger et al. (2023).

Outline. The remainder of this paper is organized as follows. Section 2 presents the production model. Section 3 discusses the empirical strategy and identification. Section 4 introduces the data and discusses the selected measures. Section 5 presents the results. Section 6 concludes.

2 The Meaning Production Function

The model builds on theoretical work by Martela and Riekki (2018) and Cassar and Meier (2018), who argue that meaning can be created through both social- and non-social impact. The latter is captured by the three needs of Ryan and Deci (2000)'s self determination theory – autonomy, competence, and relatedness. As proposed in Cassar and Meier (2018), we model the level of work meaning as a production process with the different pathways as its inputs. But unlike their model, we abstract from the effort margin, which aligns closer with models from the psychology literature, such as Rosso et al. (2010) and Martela and Riekki (2018). We write the production function of meaning as:

$$M_i = f\left(S_i,\quad \underbrace{A_i, C_i, R_i,}_{\text{non-social impact}}\quad \eta_i\right), \tag{1}$$

where M_i represents the experienced level of *work meaning* for individual i, S_i their perceived level of social impact, and A_i, C_i, R_i the perceived level of the different aspects of *non-social impact*, being *autonomy*, *competence*, and *relatedness*. The final term η_i represents an idiosyncratic productivity shock that captures the effect of potentially omitted inputs.

We parameterize the production process as trans-log to allow for flexible substitution patterns between the different pathways. An important benefit of this functional form over the commonly used Constant Elasticity of Substitution (CES) functions are that it does not impose prior restrictions on the nature of substitution patterns (Agostinelli and Wiswall, 2025). This allows, for example, the social impact component of meaning to be either more, or less, productive at different levels of non-social impact. The production function equation (1) becomes:

$$\ln M_i = \sum_{P\in\mathcal{P}} \gamma_P \ln(P_i) + \sum_{P\in\mathcal{P}} \sum_{\substack{P'\in\mathcal{P} \\ P'\neq P}} \gamma_{PP'} \left(\ln(P_i) \times \ln(P'_i)\right) + \eta_i, \tag{2}$$

where $\mathcal{P} = \{S, A, C, R\}$ denotes the set of pathways. With normalized inputs, the γ_P coefficients represent the direct output elasticity of work meaning with respect to pathway P. The $\gamma_{PP'}$ coefficients on the interaction terms are pair-specific complementarities between pathways P and P'[2].

3 Empirical Strategy

Measurement Model. Both work meaning and the different pathways are difficult concepts to measure. To address this issue, we follow the literature that estimates human capital production functions, and introduce a measurement system (Cunha and Heckman, 2007; Cunha et al., 2010). Suppose that we have different observed measures for each pathway. The latent pathways are then assumed to be related to the observed measures through a log-linear measurement model

[2]Note that $\ln(P_i) \times \ln(P'_i)$ and $\ln(P'_i) \times \ln(P_i)$ are the same, but we of course include each interaction only once.

with the following structure[3]:

$$Q_j^F = \mu_j^F + \lambda_j^F \ln F + \psi_j^F \text{ for all } F \in \{\mathcal{P} \cup M\}, \tag{3}$$

where Q_j^F is the j-th measure of the latent pathway F, μ_j^F is the location of the measure, λ_j^F the loading of the j-th measure of the latent pathway, and ψ_j^F a measure-specific error term. The error terms are assumed to be mean zero and independent of each other, the latent pathways, and the production shocks η_i.

The loading of the first measure of each latent pathway (λ_1^F) is normalized to unity without loss of generality. Additionally, we normalize the logarithm of all latent pathways $\ln(F)$ to be mean zero. Given these normalizations, we can retrieve the loadings by taking the sample analog of:

$$\lambda_j^F = \frac{\text{Cov}(Q_j^F, Q_{j'}^F)}{\text{Cov}(Q_1^F, Q_{j'}^F)} \text{ for all } j \neq j' \text{ and } F \in \{\mathcal{P} \cup \mathcal{M}\}, \tag{4}$$

$$\mu_j^F = \mathbb{E}(Q_j^F) \text{ for all } j \text{ and } F \in \{\mathcal{P} \cup M\}. \tag{5}$$

We then use these estimates to construct the following measures of the latent pathways:

$$\widetilde{\ln F}_j = \frac{Q_j^F - \mu_j^F}{\lambda_j^F} \text{ for all } j \text{ and } F \in \{\mathcal{P} \cup M\},$$

which we use to estimate the production function. Note that for these measures, the following equality holds:

$$\ln F + \frac{\psi_j^F}{\lambda_j^F} = \frac{Q_j^F - \mu_j^F}{\lambda_j^F} = \widetilde{\ln F}_j, \text{ for all } F \in \{\mathcal{P} \cup M\}. \tag{6}$$

Estimation. We write our production function by substituting in the pathways that we constructed using equation (6). As shown in Agostinelli and Wiswall (2025), this can be rewritten

[3] The assumption is clearly not without loss of generality. But as pointed out in Agostinelli and Wiswall (2025), it is made in most empirical work on human capital production – see Cunha et al. (2021) for an overview of this research. Also note that the latent distributions of each factor can be identified with three or more dedicated measures – see for example Cunha et al. (2010).

into (details in Appendix A.1):

$$\widetilde{\ln M}_{ij} = \sum_{P \in \mathcal{P}} \gamma_P \widetilde{\ln P}_{ij} + \sum_{P \in \mathcal{P}} \sum_{\substack{P' \in \mathcal{P} \\ P' \neq P}} \gamma_{PP'} \left(\widetilde{\ln P}_{ij} \times \widetilde{\ln P'}_{ij} \right) + \phi_i + \phi_o + \xi_{ij}(\widetilde{\ln P}_{ij}, \widetilde{\ln P'}_{ij}). \quad (7)$$

The error term in this equation (ξ_{ij}) is correlated with the pathways, so we cannot directly use an ordinary least squares estimator. However, as noted in Agostinelli and Wiswall (2025), alternative omitted measures of the latent pathways are valid instruments. They are relevant by definition, and uncorrelated with all components of ξ_{ij} under the measurement model assumptions. We also introduce both individual (ϕ_i) and occupation (ϕ_o) fixed effects into the production function.

Because of the two-step nature of the estimation strategy, we rely on a bootstrapping procedure for inference. Since we do not want to make an arbitrary choice regarding which measures to include in the measurement model and which to use as instruments, we cycle through all possible choices.[4] We then estimate the production function for each of these choices, to obtain a distribution of estimates. We perform a block bootstrap on the individual level, where we draw the same number of individuals as in our main sample with replacement, and report means and confidence bounds of the bootstrapped parameter distributions.

Identification. We rely on within-individual variation in work meaning and the pathways to identify the production function by introducing individual fixed effects. On the one hand, this addresses concerns related to how respondents interpret the answer scales. The idiosyncratic interpretations of questions and answers could be driven by latent personality traits, which may be omitted factors in the production function. This problem is well known in the broader literature on subjective well-being (Ferrer-i Carbonell and Frijters, 2004). On the other hand, this also accounts for issues that are often raised in the literature on compensating differentials (Rosen, 1986; Lavetti, 2023). Job amenities tend to come bundled, and more productive individuals work jobs that are better in several dimensions (Hamermesh, 1999). Some of these characteristics (e.g., job security) are unobserved, but could be omitted factors in the production function. Controlling for time invariant differences in productivity largely addresses these concerns. Finally,

[4]After controlling for measurement error, the normalization in equation (4) does not influence the estimation. We therefore do not cycle through this normalization.

we want to highlight that different perceptions of meaning and the pathways are driven by both changes within (e.g., in tasks or environment) and between jobs. We use both sources of variation to identify the production function coefficients. The summary statistics in Appendix B.1 show that only a minority of respondents changes employer (10%) or supervisor (30%).

4 Data

We estimate the model using data from the American Working Conditions Survey (AWCS). The AWCS is collected by Maestas et al. (2023) through the American Life Panel (ALP), a representative survey of workers in the United States conducted by the RAND Corporation. The questions are modeled after those in the European Working Conditions Surveys (EWCS). An important benefit compared to other surveys is that there are additional questions about several pathways, and that there are four waves of data on the same sample of workers, collected between 2015 and 2018. We construct a panel of all individuals that participated in at least two waves, and end up with almost 5.000 observations for more than 1.600 individuals without any missing values. Summary statistics of our sample can be found in Appendix B.1, where we show that demographic characteristics align well with those reported in the Current Population Survey (CPS).

Description of the Measures. This subsection discusses the measures we use to capture the latent concepts of *work meaning*, *social impact*, *autonomy*, *competence* and *relatedness*. We provide an overview of all the measures in Table 1. All variables are re-coded such that higher values always indicate either more work meaning or higher perceived levels of the different pathways.

Work Meaning. The standard questionnaire used to measure work meaning in psychology is the Work and Meaning Inventory (WAMI) constructed by Steger et al. (2012). We consider how our measures relate to their conceptualization. The first measure on work meaning asks respondents about whether they have the feeling of doing useful work. This captures the *greater good motivation* and *positive meaning* dimensions. The other two measures ask respondents whether their work provides them with a feeling of work well done, and whether their job provides them with a sense of personal accomplishment. These questions capture the *meaning making through work*

Table 1: Measures of Work Meaning and Pathways

Item	Description	Mean (sd)
Meaning (M)		
$Q^{M}_{UsefulWork}$	"You have the feeling of doing useful work". Measured on a five point scale from "Always" to "Never"	2.80 (1.00)
$Q^{M}_{WorkWellDone}$	"Your job provides satisfaction of work well done". Measured on a five point scale from "Always" to "Never"	2.76 (0.97)
$Q^{M}_{PersAccomplish}$	"Your job provides you with a sense of personal accomplishment". Measured on a five point scale from "Always" to "Never"	2.70 (1.01)
Social Impact (S)		
$Q^{S}_{ImpactSociety}$	"Your work allows you to make a positive impact on society". Measured on a five point scale from "Always" to "Never"	2.50 (1.18)
Autonomy (A)		
$Q^{A}_{ApplyOwnIdeas}$	"You are able to apply your own ideas in your work." Measured on a five point scale from "Always" to "Never"	2.58 (1.07)
$Q^{A}_{SetSchedule}$	"Can you take breaks when wanted" Measured on a five point scale from "Always" to "Never"	2.53 (1.26)
$Q^{A}_{OrgInvolvement}$	"You are involved in improving work organization/processes." Measured on a five point scale from "Always" to "Never"	2.30 (1.22)
Competence (C)		
$Q^{C}_{OpportunityTalents}$	"Your job provides you with opportunities to fully use talents". Measured on a five point scale from "Always" to "Never"	2.50 (1.07)
$Q^{C}_{SolveProblems}$	"Generally, does your main paid job involve solving unforeseen problems on your own?" Measured by a Yes / No indicator	0.88 (0.38)
$Q^{C}_{ComplexTasks}$	"Generally, does your main paid job involve complex tasks?" Measured by a Yes / No indicator	0.76 (0.46)
$Q^{C}_{NewThings}$	"Generally, does your main paid job involve learning new things?" Measured by a Yes / No indicator	0.83 (0.38)
Relatedness (R)		
$Q^{R}_{ManagementAppreciate}$	"Employees are appreciated when they have done a good job". Measured on a five point scale from "Strongly Agree" to "Strongly Disagree"	2.63 (1.10)
$Q^{R}_{CooperationColleagues}$	"There is good cooperation between you and your colleagues". Measured on a five point scale from "Strongly Agree" to "Strongly Disagree"	2.99 (0.91)
$Q^{R}_{ConflictResolution}$	"Conflicts are resolved fairly" Measured on a five point scale from "Strongly Agree" to "Strongly Disagree"	2.59 (1.02)
$Q^{R}_{LikeRespectColleagues}$	"You like and respect your colleagues". Measured on a five point scale from "Strongly Agree" to "Strongly Disagree"	3.03 (0.84)

Notes. This table provides an overview of the measures of *work meaning*, *social impact*, *autonomy*, *competence*, and *relatedness* in the American Working Conditions Survey (AWCS) available in waves 2015 to 2018. The final column shows the weighted sample means and standard deviations of each measure.

dimension, which is important for personal growth. Similar questions are used as measures of work meaning in Green and Mostafa (2012) and Nikolova and Cnossen (2020).

Social Impact. There is a single measure of social impact in the survey, which asks respondents whether their work allows them to make a positive impact on society. This is a standard measure that has been used various times (see e.g., Kesternich et al. (2021), Burbano et al. (2024), and De Schouwer and Kesternich (2024)). Note that because we have only a single measure, we do not include social impact in the measurement system.

Autonomy. The measures of autonomy in our data capture control over the methods of work and over scheduling. To assess control over work methods, we rely on questions that ask respondents whether they can apply their own ideas in their work, and if they are involved in improving the organization and processes of their work. The final question captures autonomy over the work schedule, and asks respondents about their ability to take breaks when they want to. These measures are close to those used in Nikolova and Cnossen (2020) and Burbano et al. (2023).

Competence. We use four questions to measure feelings of competence among the respondents in our sample. The first question asks respondents whether their job provides them with opportunities to fully use their talents. This directly measures subjective feelings of competence. The next two measures are again similar to those used in Nikolova and Cnossen (2020). These ask respondents about whether they feel like their job involves learning new things and solving unforeseen problems. Finally, we also include a question about whether respondents feel like their jobs involve complex tasks.

Relatedness. The measures of relatedness capture whether respondents feel connected to their colleagues and to the company. The first set of measures asks respondents whether employees are appreciated when they have done a good job, whether there is good cooperation with colleagues, and whether they like and respect their colleagues. The final question aims to capture more general relatedness to the work environment, and asks respondents about their beliefs regarding the resolution of conflicts in the workplace. These questions are again comparable to those used in previous work by Nikolova and Cnossen (2020) and Burbano et al. (2023).

5 Results

Production Function. We now discuss the main production function estimates shown in Table 2. The first two columns present estimates without individual fixed effects, that respectively do not and do allow for pathway interactions. The final two columns are similar, but for models with individual fixed effects. The first thing to note is that, across all specifications, each pathway positively enters the production function. This highlights that there are several ways to create meaning at work. We also seem to capture a large fraction of the variance in meaning, since our preferred specification with fixed effects and interactions – see column (4) – explains roughly 83% of the variation in meaning between-, and 48% within-individuals. These results are in line with the theoretical predictions and correlations documented in the literature (Cassar and Meier, 2018; Martela and Riekki, 2018).

But there are substantial differences in how effective the different pathways are. Across all models, pro social impact is the most effective. In our preferred specification, we estimate a direct output elasticity of 0.543. The second and third most effective pathways are relatedness and autonomy, with direct out elasticities of 0.127 and 0.150 respectively. Finally, we find competence to be the least effective pathway, with a direct output elasticity of 0.04.

We show that accounting for individual heterogeneity generally reduces the effectiveness of each pathway. Comparing our main specification to the same model without fixed effects – see column (2) – point estimates decrease. For social impact, we find that the coefficient is about 10% smaller, and for non-social impact we find even larger differences in the effectiveness of competence and relatedness, which decreases by about 30% each. As discussed before, this may be due to idiosyncrasies in the interpretation of answer scales (Ferrer-i Carbonell and Frijters, 2004) or because of other amenities that people find meaningful and that we control for by removing time-constant productivity differences (Lavetti, 2023).

The next main result from our analysis is that interactions between the different pathways are important, as argued in Cassar and Meier (2018). Notably, we find that social impact interacts negatively with all non-social impact variables. The negative interaction is the largest with autonomy (0.082), followed by relatedness (0.050) and competence (0.041). This highlights that social impact could be a particularly efficient source of meaning when perceived non-social im-

Table 2: Production Function Parameters

	(1)	(2)	(3)	(4)
Social Impact	**0.621**	**0.609**	**0.574**	**0.543**
	(0.533, 0.708)	(0.524, 0.694)	(0.478, 0.682)	(0.446, 0.641)
Autonomy	**0.145**	**0.144**	**0.159**	**0.150**
	(0.056, 0.219)	(0.060, 0.212)	(0.069, 0.252)	(0.068, 0.236)
Competence	0.054	0.059	0.043	0.040
	(-0.035, 0.209)	(-0.029, 0.219)	(-0.066, 0.170)	(-0.079, 0.182)
Relatedness	**0.196**	**0.191**	**0.137**	**0.127**
	(0.106, 0.277)	(0.109, 0.272)	(0.061, 0.210)	(0.053, 0.197)
Social Impact × Autonomy		*-0.061*		**-0.082**
		(-0.128, 0.003)		(-0.158, -0.012)
Social Impact × Competence		-0.016		-0.041
		(-0.072, 0.042)		(-0.126, 0.039)
Social Impact × Relatedness		-0.017		-0.050
		(-0.085, 0.060)		(-0.115, 0.011)
Autonomy × Competence		0.034		0.009
		(-0.017, 0.090)		(-0.073, 0.091)
Autonomy × Relatedness		0.001		0.009
		(-0.058, 0.064)		(-0.055, 0.079)
Competence × Relatedness		-0.007		-0.014
		(-0.068, 0.051)		(-0.086, 0.053)
Adjusted R^2	**0.595**	**0.604**	**0.822**	**0.831**
	(0.531, 0.655)	(0.538, 0.665)	(0.783, 0.866)	(0.793, 0.872)
Within R^2			**0.455**	**0.481**
			(0.367, 0.536)	(0.393, 0.563)
Number of observations	4858	4858	4858	4858
Individual FE	No	No	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes

Notes. Point estimates of the production function parameters – the values of γ_P and $\gamma_{PP'}$ from equation (7) – for specifications with and without interactions, individual, and occupation fixed effects. Below each estimate, we present 95% bootstrapped confidence bounds based on 100 bootstrap samples. Bold faced estimates are significant at the 5% level. See Appendix C for the complete results.

pact is lacking, and vice versa. On the other hand, we find no evidence of interactions between competence, relatedness, and autonomy themselves.

Robustness. We highlight several features related to the robustness of our findings in Appendix D. We first present the full coefficient distribution from all bootstrapped regressions in Figure A.2. This shows that the results do vary somewhat across measures, highlighting the benefit of our agnostic approach. The second robustness check is in line with the effects of effort discussed in Cassar and Meier (2018). Table A.7 shows the results from restricting our sample to full-time workers only. Differences in the estimated coefficients are small, with the only exception being the effect of competence. In the sample of full-time workers, the direct elasticity of competence is about twice as large, so feelings of competence and skill use matter more when time spent working increases. The third robustness check in Table A.8 studies the importance of accounting for measurement error. As in Agostinelli and Wiswall (2025), we re-run our analysis without instrumenting the pathways. While there are no clear predictions on the sign of the bias – because of the non-linearities and various interrelated equations in the model – we find significant evidence of attenuation. Comparing our main specification in both cases, we find that almost all point estimates move towards zero. While the differences in these coefficients are not statistically significant, we find that the direct elasticities of social impact (7.4%), autonomy (43.4%), and competence (29.9%) are all notably smaller. The effect of competence on the other hand seems to increase, but confidence bounds are very wide here.

5.1 Money Metric Benefits

The production function estimates provide us with a useful indication for the direction and significance of the different pathways in generating work meaning. To better understand the magnitude of these findings, we translate meaning into monetary terms. We do so by estimating the equilibrium price of work meaning – the *compensating differential* as in Rosen (1986) – and then calculate how much dollars a change in social and non-social impact generates.

Pricing Work Meaning. To estimate the equilibrium price of work meaning, we need to address the endogeneity of meaning with respect to wages. The issue is that workers of different productivity levels divide their total compensation differently between money and meaning, and more productive workers end up with higher levels of both. Because productivity is difficult to control for, naive compensating differentials estimates are biased and typically even 'wrong-signed' – see Hwang et al. (1992) for an early discussion. To address this problem, we use an estimator recently introduced by Bell (2024).[5] The approach relies on observing an imprecise proxy for ability to shift workers' total compensation.

The Bell (2024) estimator consists of two step. The first stage regresses meaning and monthly wages on an observed ability proxy. In our case, the available proxy is years of education. This

[5]See Folke and Rickne (2022), Burbano et al. (2023), Bell et al. (2024), and De Schouwer and Kesternich (2024) for recent uses of the estimator.

regression essentially determines the direction in which productivity increases. We then use the predicted values from the first-stage regression as controls in the second stage regression of work meaning on wages. The coefficient on meaning in the second stage regression – ψ_m below – can be interpreted as the compensating differential, under the assumption that the proxy variable is (i) informative about total compensation, but (ii) not related to how workers *split* their total compensation into meaning and wages. General measures of productivity that are not specifically manipulated to obtain jobs with different meaning and money combinations – we follow the literature in using years of education – satisfy these assumptions. The regressions that we estimate are:

$$\text{First-Stage:} \quad S_i = \theta_M \ln(M_i) + \theta_W W_i + \xi_i \tag{8}$$

$$\text{Second-Stage:} \quad W_i = \psi_M \ln(M_i) + \psi_S \hat{S}_i + \epsilon_i, \tag{9}$$

where S_i denotes years of schooling, M_i the level of meaning derived from our measurement model, and W_i monthly wages.

Table 3: The Price of Work Meaning (in dollars)

	Base	Productivity Controls	Bell Proxy
Meaning	-17.26 (-93.00 , 58.48)	-57.02 (-126.85, 12.81)	**-218.05** (-35.21 , -402.78)
Partial F			1024.47

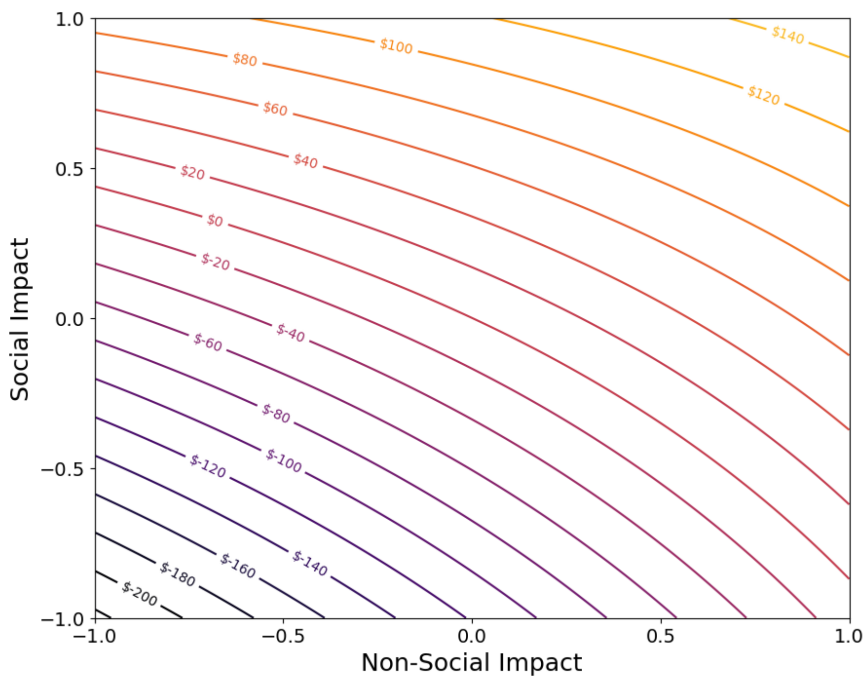
Notes. Coefficients from regressions of meaning on monthly wages. The Base specification contains no control variables, we then introduce productivity controls (years of education), and finally the Bell estimates as discussed in section 5.1. We report 95% confidence intervals, which are derived from T-tests (for the base and productivity specifications) and Anderson-Rubin tests (for the Bell estimates) as discussed in Andrews et al. (2019) and Bell (2024). The Partial F statistic from the first stage regression is presented in the final row. First-Stage results can be found in Appendix C.

The compensating differential estimates are shown in Table 3.[6] We first estimate a simple linear regression of work meaning on wages without the ability proxy as a control (see Base column). This leads to a small and insignificant estimate of less than 20 dollars, confounded by

[6] We show the average across our three measures of meaning, separate estimates are in Appendix C.

productivity differences. Introducing a noisy ability control (see Productivity Controls column) does little to address this problem. The final column (Bell Proxy) presents estimates from the Bell (2024) estimator described above. We find that the equilibrium price of a standard deviation increase in work meaning is worth almost 220 dollars of monthly wages, or about 4.7%, which is significant at the 95% level.[7] This estimate is broadly in line with the literature. Previous work by Burbano et al. (2023) finds compensating differential for meaning in Sweden to be between 4 and 5%. In the same dataset, Maestas et al. (2023) finds a willingness to pay for social impact of about 3.6%. Similar valuations are reported in De Schouwer and Kesternich (2024) for the Netherlands.

Figure 1: Money Metric Benefits (monthly salary in $)



Notes. Monetary values, priced in terms of an equilibrium compensating differential in the labor market, for different changes in social and non-social impact. These numbers are based on the production function estimates for our main specification presented in column (4) of Table 2 and the Bell (2024) compensating differential estimate in column (3) of Table 3.

The Monetary Value of Social and Non-Social Impact. We now compute the value generated by a standard deviation change in either social or non-social impact, with the latter summing up the individual effects from autonomy, relatedness, and competence. The result is shown in

[7] Two estimates are significant at the 95% level and one at 90%.

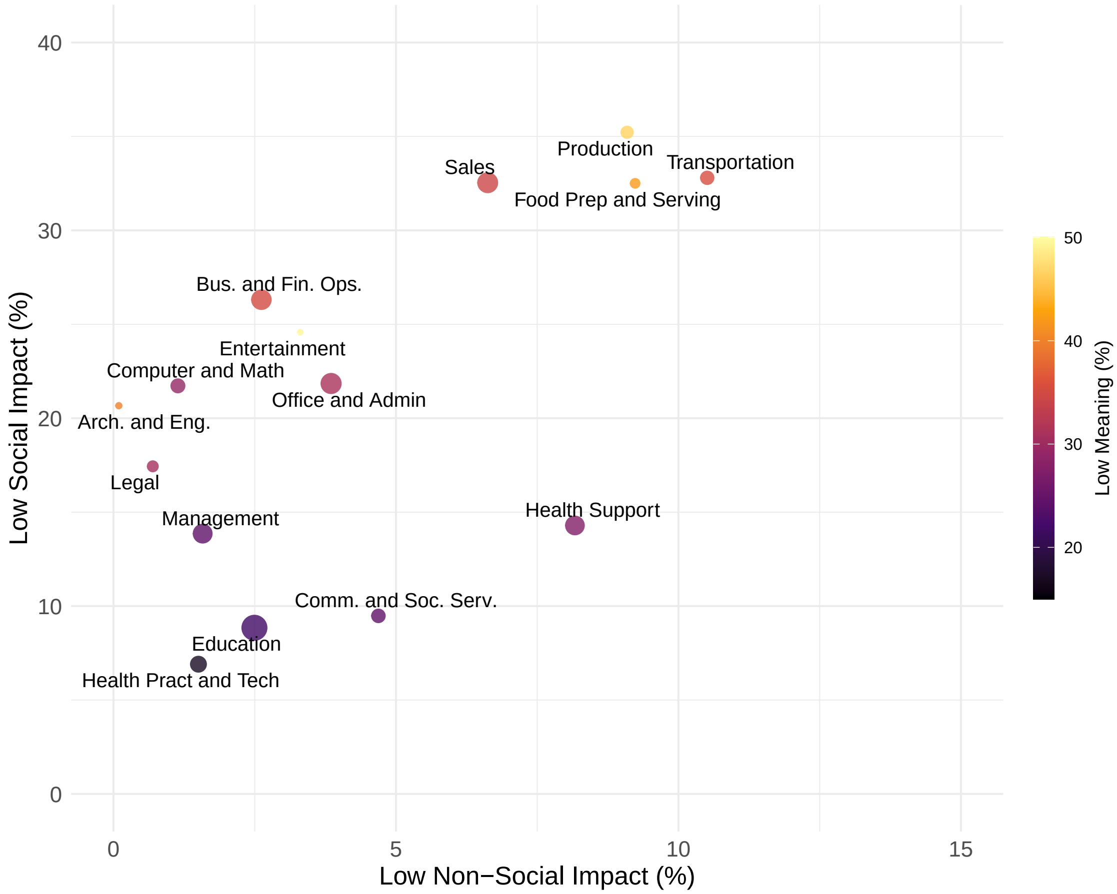
Figure 1. The curvature of these level lines highlights the degree of substitution between the two dimensions. We find that, on average, an increase in social impact is equivalent to a monthly salary increase of about 118 dollars, and an increase in non-social impact is equivalent to about 70 dollars. But the effectiveness of these changes is largely determined by the negative interaction. A standard deviation increase in social impact is twice as effective in creating meaning for individuals that perceive their jobs as having little non-social impact (one standard deviation below the mean), where it is valued at almost 160 dollars, compared to those with high perceived non-social impact (one standard deviation above), where it is valued at just 80 dollars. This suggests that a lot of value can be created by increasing the social impact for workers with only little perceived non-social impact.

5.2 Impact Across Occupations

The final step in our analysis is to consider occupational differences in social and non-social impact, shown in Figure 2. We find a large fraction of people in Production, Transportation, Food Preparation and Serving, and Sales that report low levels of social (30%) and non-social (10%) impact. These are also the occupations where a large fraction reports low levels of meaning – up to almost 50% for Production workers. Based on our findings, increasing the social impact in these jobs would generate substantial benefits for these workers. These results can be related to Dur and van Lent (2019), who find that a high percentage of individuals that work as plant and machine operators, and cooks, waiters or bartenders consider their jobs to be socially useless.

We also find that Health Support and Social Service occupations are characterized by high social impact but relatively low non-social impactt. In these occupations there may be room to further improve non-social impact, which could generate as much as further improving social impact. Technological advances may help raise autonomy, for example by improving control over schedules, as documented for pharmacists by Goldin and Katz (2016). On the other hand, we find that several high-skill occupations, such as those in Business and Law, Computer and Mathematics, and Office and Administration, report high non-social impact, but not always high social impact. Increasing social impact in these occupations will be beneficial, but will not generate as much value as in the group of low non-social impact occupations.

Figure 2: Social and Non-Social Impact across Occupations



Notes. This figure highlights the fraction of workers that considers their jobs as having little social and non-social impact, defined as being half of a standard deviation below the mean, across occupations. Colors indicate the fraction that considers their jobs to have low meaning, also measured as at least half a standard deviation below the mean. The size of each dots indicates the number of people in each occupation in our sample. We show only the fifteen biggest occupations for readability.

6 Conclusion

This paper studies what makes work meaningful. We do so by estimating a within-individual production function for work meaning, which takes the pathways identified in theoretical work – social impact, and non-social impact as measured through autonomy, competence, and relatedness – as its inputs. We find that work meaning can be created through all pathways, but that social impact is the most effective. In monetary terms, a standard deviation increase in social impact is worth between 80 and 150 dollars, depending on the level of non-social impact. These results highlight both the significance of work meaning, and how it can be effectively created through different pathways across occupations.

An interesting direction for future work would be to study further the importance of heterogeneity in the production process. Because we rely on fixed effects to estimate our parameters, we cannot study the main dimensions of heterogeneity that have previously been highlighted. For example, several recent papers highlight that women experience higher levels of social impact in their jobs (Burbano et al., 2023; De Schouwer and Kesternich, 2024). One possible explanation for these differences is that social impact is a more efficient pathway to meaning for women than it is for men. Another direction is to further extend the production model, for example by modeling effort as an additional input as suggested in Cassar and Meier (2018). Doing so would allow us to further study how work meaning and labor supply are related,

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A Appendix

A.1 Model Equations

We present the omitted equations from the main text below. Note that substituting the residual measures defined by equation (6) into our production function defined by equation (2) yields:

$$\widetilde{\ln M}_{ij} - \tilde{\psi}_{ij}^{M} = \sum_{P \in \mathcal{P}} \gamma_P (\widetilde{\ln P}_{ij} - \tilde{\psi}_{ij}^{P}) + \sum_{P \in \mathcal{P}} \sum_{\substack{P' \in \mathcal{P} \\ P' \neq P}} \gamma_{PP'} (\widetilde{\ln P}_{ij} - \tilde{\psi}_{ij}^{P})(\widetilde{\ln P'}_{ij} - \tilde{\psi}_{ij}^{P'}) + \phi_i + \phi_o + \eta_{ij},$$

where $\tilde{\psi}_{ij}^{F} = \psi_{ij}^{F} / \lambda_j^{F}$, for $F \in \{\mathcal{P} \cup M\}$. We re-arrange this into equation (7) of the main text, with the equation for the error term (ξ_{ij}) then being:

$$\xi_{ij} = \eta_{ij} + \tilde{\psi}_{ij}^{M} - \Big[\sum_{P \in \mathcal{P}} \gamma_P \tilde{\psi}_{ij}^{P} \Big] + \sum_{P \in \mathcal{P}} \sum_{\substack{P' \in \mathcal{P} \\ P' \neq P}} \gamma_{PP'} \Big[\tilde{\psi}_{ij}^{P} \cdot \tilde{\psi}_{ij}^{P'} - \widetilde{\ln P}_i \cdot \tilde{\psi}_{ij}^{P} - \widetilde{\ln P'}_i \cdot \tilde{\psi}_{ij}^{P} \Big]. \tag{10}$$

A.2 Estimation Procedure

The first-stage regressions we run are of the form:

$$\widetilde{\ln F^i} = \beta_{ij}^{F} Q_j^{F} + \nu_j \text{ for all } F \in \{\mathcal{P} \cup M\} \text{ and with } j \neq k. \tag{11}$$

We use this to predict $\widehat{\ln F}$, which is the measure cleansed of measurement error. The production function thus becomes:

$$\widehat{\ln M}_{ij} = \sum_{P \in \mathcal{P}} \gamma_P \widehat{\ln P}_{ij} + \sum_{P \in \mathcal{P}} \sum_{\substack{P' \in \mathcal{P} \\ P' \neq P}} \gamma_{PP'} \left(\widehat{\ln P}_{ij} \times \widehat{\ln P'}_{ij} \right) + \phi_i + \phi_o + \epsilon, \tag{12}$$

where ϵ is uncorrelated with the pathways.

B Summary Statistics and Exploratory Analysis

B.1 Sample Summary Statistics

Table A.1 compares the main demographics in our sample to those found in the Current Population Survey for 2015. We use the sample weights constructed by Maestas et al. (2017). We find that our sample is generally representative in terms of demographics, as ages, gender, and education levels line up well. We also find that the labor market outcomes are close in terms of both the hours worked and earnings reported in the Current Population Survey.

Table A.1: Sample Summary Statistics.

	CPS	AWCS
Demographics		
Fraction Age 25–34	23.2	22.3
Fraction Age 35–49	32.7	27.0
Fraction Female	51.4	47.0
Fraction High School or Less	37.6	33.9
Fraction some college or Associate's	28.2	28.4
Fraction bachelor's +	34.2	37.7
Labor Market		
Fraction working part time (hours < 35)	14.8	16.5
Average weekly hours (main job)	39.8	40.0
Average weekly hours (all jobs)	39.7	40.0
Median monthly earnings (main job, in k$)	3.33	3.67
Average monthly earnings (main job, in k$)	4.41	4.4
Average number of waves (unweighted)		3.06
Number of Individuals		1,588
Share with Same Employer (%)		89.02
Share with Same Boss (%)		72.15

Notes. This table presents the summary statistics for our sample, and compares them to demographics from the Current Population Survey as reported in Maestas et al. (2017).

B.2 Measures

This appendix first discusses briefly the distribution of measures, and then shows the results from an Exploratory Factor Analysis (EFA). The distributions of our measures is shown in Table A.2. The main takeaway is that we generally have a substantial amount of variation in all our measures. This is true even for measures regarding the usefulness of individuals' jobs, where the standard deviation is about one, and a substantial fraction of more than 25% of respondents indicates rather low levels of usefulness. The same is true for the measures of impact on society. We find that the fraction of individuals reporting only a minimal positive impact on society is more than 10%.

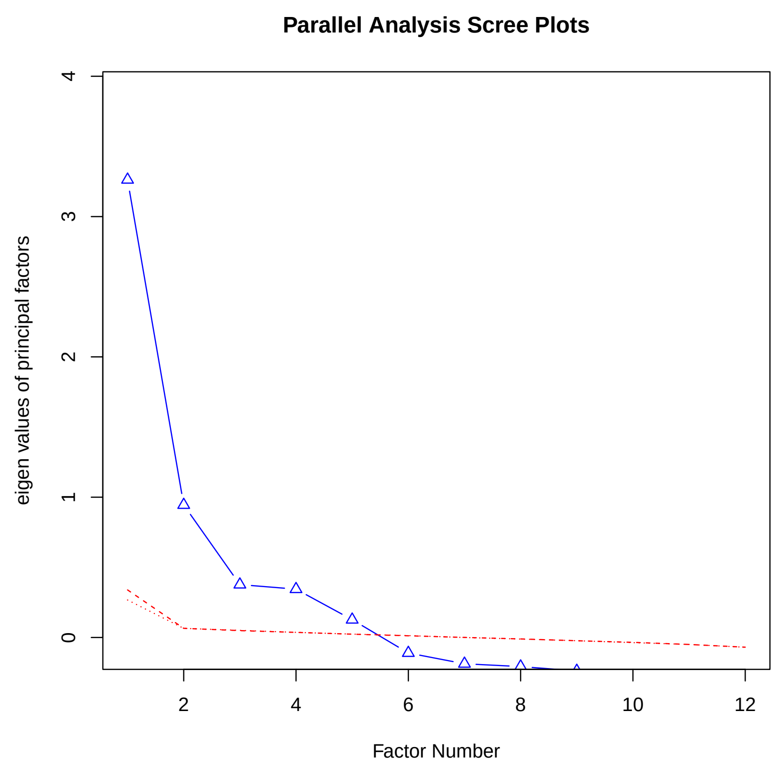
Table A.2: Distributions of the Measures.

	Mean	Std. Dev.	10%	25%	50%	75%	90%
Work Meaning (M)							
$Q^{M}_{UsefulWork}$	2.80	1.00	2.00	2.00	3.00	4.00	4.00
$Q^{M}_{WorkWellDone}$	2.76	0.97	2.00	2.00	3.00	3.00	4.00
$Q^{M}_{PersAccomplish}$	2.70	1.01	1.00	2.00	3.00	3.00	4.00
Social Impact (S)							
$Q^{S}_{ImpactSociety}$	2.50	1.18	1.00	2.00	3.00	3.00	4.00
Autonomy (A)							
$Q^{A}_{ApplyOwnIdeas}$	2.58	1.07	1.00	2.00	3.00	3.00	4.00
$Q^{A}_{SetSchedule}$	2.53	1.26	0.70	2.00	3.00	4.00	4.00
$Q^{A}_{OrgInvolvement}$	2.30	1.22	0.00	2.00	2.00	3.00	4.00
Competence (C)							
$Q^{C}_{OpportunityTalents}$	2.50	1.07	1.00	2.00	3.00	3.00	4.00
$Q^{C}_{SolveProblems}$	0.88	0.38	0.00	1.00	1.00	1.00	1.00
$Q^{C}_{ComplexTasks}$	0.76	0.46	0.00	0.00	1.00	1.00	1.00
$Q^{C}_{NewThings}$	0.83	0.38	0.00	1.00	1.00	1.00	1.00
Relatedness (R)							
$Q^{R}_{ManagementAppreciate}$	2.63	1.10	1.00	2.00	3.00	3.00	4.00
$Q^{R}_{CooperationColleagues}$	2.99	0.91	2.00	3.00	3.00	4.00	4.00
$Q^{R}_{ConflictResolution}$	2.59	1.02	1.00	2.00	3.00	3.00	4.00
$Q^{R}_{LikeRespectColleagues}$	3.03	0.84	2.00	3.00	3.00	4.00	4.00

Notes. Distribution of the different measures of work meaning, social impact, autonomy, competence, and relatedness in the American Working Conditions Survey (AWCS).

The variation in these measures is important, and addresses the concern that everyone could find their own work to be extremely useful or beneficial. On the other hand, it also suggests that socially desirable answers are not a large problem. We find that the variance is the lowest for our binary measures. For example, the measures about whether an individual learns new things or whether their job features solving complex tasks, contain a little less, but still a reasonable amount of variation, with 83% and 76% of individuals respectively responding positively.

Figure A.1: Exploratory Factor Analysis – Scree Plot



Notes. Scree plot of an Exploratory Factor Analysis to study the interrelation of the different measures of work meaning, social impact, autonomy, competence, and relatedness in the American Working Conditions Survey (AWCS).

To explore how the different measures are interrelated, we show the results from an Exploratory Factor Analysis in Table A.3. We imposed a four factor solution, in line with the theoretical model of Cassar and Meier (2018). This is generally supported by the scree plot in Figure A.1. A fifth factor could be added but would explain little additional variation. We find that the first factor captures relatedness, with all measures that we labeled as capturing relatedness having loadings between 0.5 and 0.9. The third factor captures autonomy, with all measures loading between 0.050 and 0.85. The fourth factor captures competence. Only the second factor seems to have an ambiguous interpretation, because both our social impact measure and the competence measure that assesses opportunities to use talents load highly. This is important to take into account when we looking at our dedicated measurement system.

Table A.3: Exploratory Factor Analysis – Results

	Factor 1	Factor 2	Factor 3	Factor 4
Social Impact (S)				
$Q^{S}_{ImpactSociety}$	-0.002	**0.800**	-0.049	-0.033
Autonomy (A)				
$Q^{A}_{ApplyOwnIdeas}$	-0.057	0.044	**0.845**	-0.024
$Q^{A}_{SetSchedule}$	0.011	-0.091	**0.565**	-0.029
$Q^{A}_{OrgInvolvement}$	0.021	0.071	**0.618**	0.057
Competence (C)				
$Q^{C}_{OpportunityTalents}$	-0.036	**0.873**	0.002	0.011
$Q^{C}_{SolveProblems}$	-0.004	-0.079	0.029	**0.512**
$Q^{C}_{ComplexTasks}$	-0.016	-0.016	-0.091	**0.738**
$Q^{C}_{NewThings}$	0.024	0.118	0.042	**0.371**
Relatedness (R)				
$Q^{R}_{ManagementAppreciate}$	**0.514**	0.222	0.052	-0.056
$Q^{R}_{CooperationColleagues}$	**0.907**	-0.136	-0.016	0.038
$Q^{R}_{ConflictResolution}$	**0.652**	0.100	0.009	-0.021
$Q^{R}_{LikeRespectColleagues}$	**0.854**	-0.090	-0.037	0.017

Notes. Exploratory Factor Analysis to study the interrelation of the different measures of work meaning, social impact, autonomy, competence, and relatedness in the American Working Conditions Survey (AWCS). Values greater than 0.50 in bold font.

C Model Results

C.1 Measurement System Estimates

We now look at the results of estimating the dedicated measurement system in Table A.4. This shows that all measures load in the expected direction, and that the weights for the different measures are relatively comparable. This means that the information content about the latent pathways is similar for all measures. We find no indication that the competence measure about opportunities to use talents measures something entirely different than the other measures of competence.

Table A.4: Measurement System Estimates.

	weights	intercepts
Work Meaning (M)		
$Q^M_{UsefulWork}$	1.000	2.796
$Q^M_{WorkWellDone}$	1.001	2.758
$Q^M_{PersAccomplish}$	1.053	2.704
Social Impact (S)		
$Q^S_{ImpactSociety}$	1.000	2.498
Autonomy (A)		
$Q^A_{ApplyOwnIdeas}$	1.000	2.577
$Q^A_{SetSchedule}$	0.718	2.534
$Q^A_{OrgInvolvement}$	0.918	2.302
Competence (C)		
$Q^C_{OpportunityTalents}$	1.000	2.502
$Q^C_{SolveProblems}$	0.533	0.878
$Q^C_{ComplexTasks}$	1.083	0.757
$Q^C_{NewThings}$	0.878	0.829
Relatedness (R)		
$Q^R_{ManagementAppreciate}$	1.000	2.628
$Q^R_{CooperationColleagues}$	0.947	2.986
$Q^R_{ConflictResolution}$	1.054	2.591
$Q^R_{LikeRespectColleagues}$	0.828	3.031

Notes. Results from estimating the measurement system in equations (4) and (5). using data from the American Working Conditions Survey (AWCS).

C.2 The Bell Estimator

This appendix first describes the first-stage results from the estimator by Bell (2024) discussed in section 5.1 and then shows the estimates for our different measures of meaning. We use years of education as the productivity proxy as mentioned in the main text. To price the amenities, we Winsorized the wage distribution at the top and bottom 5%. We ran the regressions on all waves combined. While the results in Table A.5 have no structural interpretation, positive signs on the coefficients reflect that these are forms of compensation that workers enjoy – as discussed in Bell (2024). We find this to be the case for both work meaning and wages for all the different measures.

Table A.5: Distributions of the Measures.

Outcome: Years of Education	$Q^M_{UsefulWork}$	$Q^M_{WorkWellDone}$	$Q^M_{PersAccomplish}$
Cons.	**14.02**	**14.02**	**14.02**
	(0.21)	(0.21)	(0.21)
Work Meaning	**0.07**	*0.04*	**0.06**
	(0.02)	(0.02)	(0.03)
Monthly Wages (in 1.000$)	**0.27**	**0.27**	**0.27**
	(0.01)	(0.01)	(0.01)
R^2	0.47	0.47	0.47
Adj. R^2	0.47	0.47	0.47
Num. obs.	4770	4770	4770
Occupation FE	Yes	Yes	Yes

Notes. First stage regression of Bell (2024) estimator outlined in section 5.1. Standard errors in parentheses. Bold-faced estimates are significant at the 5% level. Wages are expressed in thousand dollar per month. Data is from the American Working Conditions Survey (AWCS).

The compensating differentials estimates are shown in Table A.6. We find that, across the different measures of meaning, the compensating differentials look rather similar. We find the lowest value of 165 dollars of monthly salary for the question about feelings of work well done. The highest amount is associated with feelings of doing useful work, at 255 dollars. We average across these values in the main text.

Table A.6: Compensating Differentials Estimates

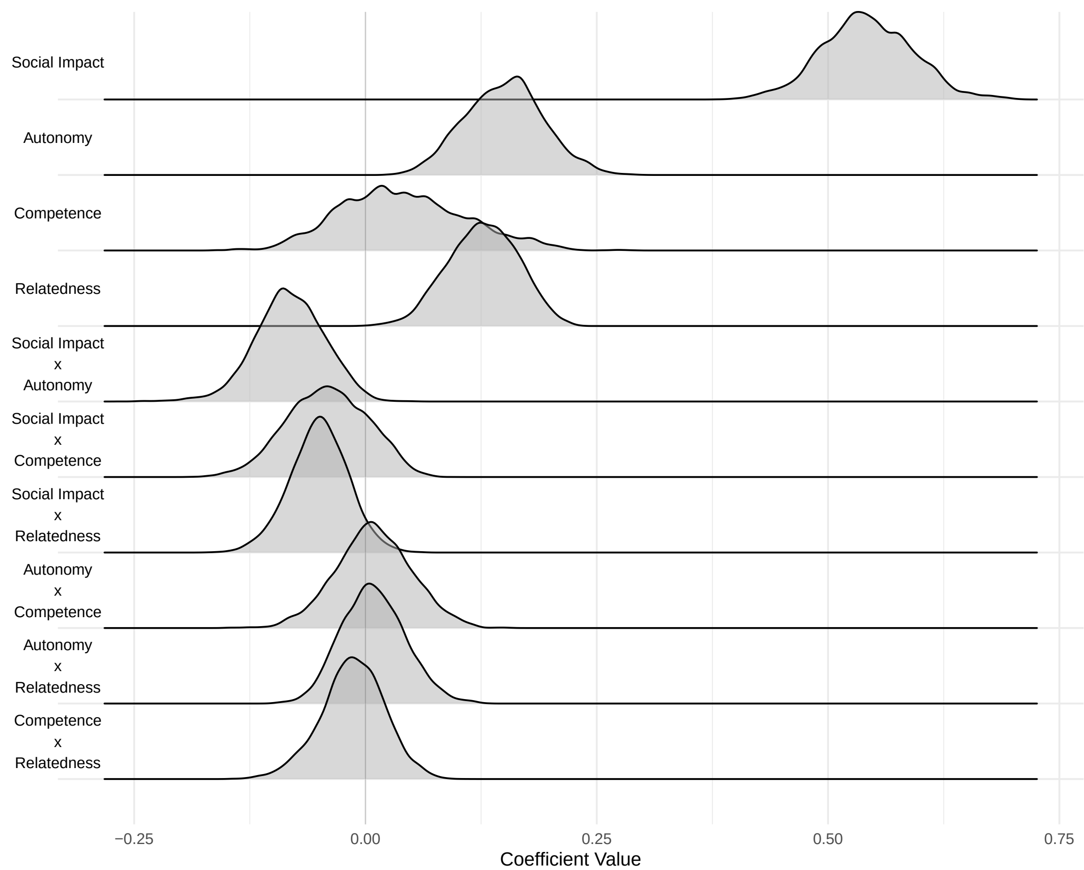
	Base	Productivity Controls	Bell Proxy	Partial F
Meaning Well Done	10.44 (-64.47 , 85.36)	-15.33 (-84.58 , 53.92)	*-165.88* (15.14 , -348.57)	1024.62
Meaning Useful	-18.06 (-93.57 , 57.44)	**-83.93** (-153.19 , -14.67)	**-255.59** (-73.34 , -440.09)	1022.26
Meaning Accomplish	-44.16 (-120.96 , 32.64)	**-71.81** (-142.79 , -0.83)	**-232.67** (-47.43 , -419.69)	1026.54

Notes. This table shows the results from estimating the compensating differentials using wage regressions and the estimator by Bell (2024) outlined in section 5.1. Data is from the American Working Conditions Survey (AWCS).

D Robustness Checks

This appendix discusses the robustness of our estimates. We first show the entire distribution of the estimated parameters in Figure A.2. We then check whether the estimates are similar in a sample of full-time workers only in Table A.7. Finally, we look at how measurement error influences our results by estimating the model without measurement error correction in Table A.8.

Figure A.2: Distribution of the Production Function Parameters



Notes. Distribution of coefficient estimates – the values of γ_P and $\gamma_{PP'}$ from equation (7) – from our main specification. Based on 100 bootstraps that cycle through all specifications. Data is from the American Working Conditions Survey (AWCS).

Table A.7: Production Function Parameters – Full Time

	(1)	(2)	(3)	(4)
Social Impact	**0.619**	**0.607**	**0.568**	**0.535**
	(0.519, 0.725)	(0.511, 0.712)	(0.453, 0.676)	(0.425, 0.640)
Autonomy	**0.146**	**0.146**	**0.134**	**0.123**
	(0.048, 0.232)	(0.053, 0.228)	(0.028, 0.258)	(0.020, 0.244)
Competence	0.051	0.056	*0.095*	*0.094*
	(-0.051, 0.239)	(-0.043, 0.245)	(-0.007, 0.241)	(-0.013, 0.254)
Relatedness	**0.200**	**0.194**	**0.127**	**0.120**
	(0.104, 0.293)	(0.108, 0.288)	(0.045, 0.207)	(0.040, 0.197)
Social Impact $\times$ Autonomy		-0.062		-0.069
		(-0.135, 0.016)		(-0.150, 0.040)
Social Impact $\times$ Competence		-0.013		-0.073
		(-0.091, 0.047)		(-0.171, 0.018)
Social Impact $\times$ Relatedness		-0.025		-0.050
		(-0.100, 0.056)		(-0.110, 0.017)
Autonomy $\times$ Competence		0.032		0.016
		(-0.032, 0.091)		(-0.064, 0.092)
Autonomy $\times$ Relatedness		0.004		-0.005
		(-0.073, 0.080)		(-0.080, 0.067)
Competence $\times$ Relatedness		-0.000		0.010
		(-0.069, 0.064)		(-0.057, 0.085)
Adjusted R^2	**0.605**	**0.616**	**0.841**	**0.849**
	(0.534, 0.675)	(0.544, 0.690)	(0.797, 0.879)	(0.807, 0.886)
Within R^2			**0.457**	**0.487**
			(0.366, 0.541)	(0.392, 0.577)
Number of observations	3906	3906	3906	3906
Individual FE	No	No	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes

Notes. Point estimates of the production function parameters – the values of γ_P and $\gamma_{PP'}$ from equation (7) – for specifications with and without interactions, individual, and occupation fixed effects. Below each estimate, we present 95% bootstrapped confidence bounds based on 100 bootstrap samples. Bold faced estimates are significant at the 5% level. Full time workers only.

Table A.8: Production Function Parameters – No Measurement Correction

	(1)	(2)	(3)	(4)
Social Impact	**0.562**	**0.554**	**0.525**	**0.503**
	(0.304, 0.709)	(0.308, 0.696)	(0.247, 0.702)	(0.241, 0.678)
Autonomy	**0.100**	**0.098**	0.090	0.085
	(0.003, 0.206)	(0.004, 0.199)	(-0.059, 0.218)	(-0.056, 0.205)
Competence	0.113	0.109	0.096	0.091
	(-0.071, 0.539)	(-0.073, 0.528)	(-0.101, 0.510)	(-0.104, 0.504)
Relatedness	**0.147**	**0.145**	**0.094**	**0.089**
	(0.022, 0.277)	(0.037, 0.275)	(0.002, 0.189)	(0.005, 0.179)
Social Impact $\times$ Autonomy		-0.042		-0.056
		(-0.126, 0.044)		(-0.172, 0.059)
Social Impact $\times$ Competence		-0.016		-0.040
		(-0.093, 0.061)		(-0.173, 0.068)
Social Impact $\times$ Relatedness		-0.014		-0.040
		(-0.091, 0.071)		(-0.118, 0.043)
Autonomy $\times$ Competence		0.008		0.004
		(-0.067, 0.080)		(-0.094, 0.108)
Autonomy $\times$ Relatedness		0.005		0.008
		(-0.069, 0.074)		(-0.089, 0.100)
Competence $\times$ Relatedness		0.001		0.003
		(-0.093, 0.087)		(-0.079, 0.098)
Adjusted R^2	**0.547**	**0.557**	**0.788**	**0.797**
	(0.443, 0.663)	(0.454, 0.674)	(0.732, 0.848)	(0.744, 0.855)
Within R^2			**0.404**	**0.429**
			(0.274, 0.532)	(0.302, 0.563)
Number of observations	4858	4858	4858	4858
Individual FE	No	No	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes

Notes. Point estimates of the production function parameters – the values of γ_P and $\gamma_{PP'}$ from equation (7) – for specifications with and without interactions, individual, and occupation fixed effects. Below each estimate, we present 95% bootstrapped confidence bounds based on 100 bootstrap samples. Bold faced estimates are significant at the 5% level. No measurement error corrections.