

# The Effectiveness of Formalization Interventions in Developing Countries<sup>1</sup>

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## Abstract.

Labor markets in developing countries are characterized by high levels of informality. A multitude of policies and programs have therefore been implemented in many countries with the objective to increase the formalization of firms or workers, or both. These formalization interventions range from information campaigns that explicate, for instance, the benefits of business registration, to the simplification of step-by-step registration procedures, to financial incentives created by reductions of payroll taxes and social security contributions, and on to interventions that enforce labor or business formalization. In this paper, we compile a database of 121 impact estimates from 28 academic studies that each evaluate empirically one or more of these formalization interventions. Using a meta analytical approach we correlate the impact estimates of the studies – given as either (i) a measure of sign and statistical significance (positive, insignificant, negative) or (ii) the percent impact as an effect size measure – with explanatory factors such as the intervention type, the outcome variable, the scope of the intervention (program or policy), and other covariates. Several key patterns emerge from the quantitative analysis: first, the intervention type is not a strong determinant for the effectiveness of formalization interventions. Second, the outcome "labor registration" shows significantly better results than other outcomes, indicating that targeting workers (relative to firms) may be a key avenue in formalization efforts. Third, interventions at scale (i.e. formalization "policies") are more effective on average than singular "programs".

JEL codes: C40, J08, J46, J48.

Keywords: Formalization, labor registration, meta analysis, impact evaluation.

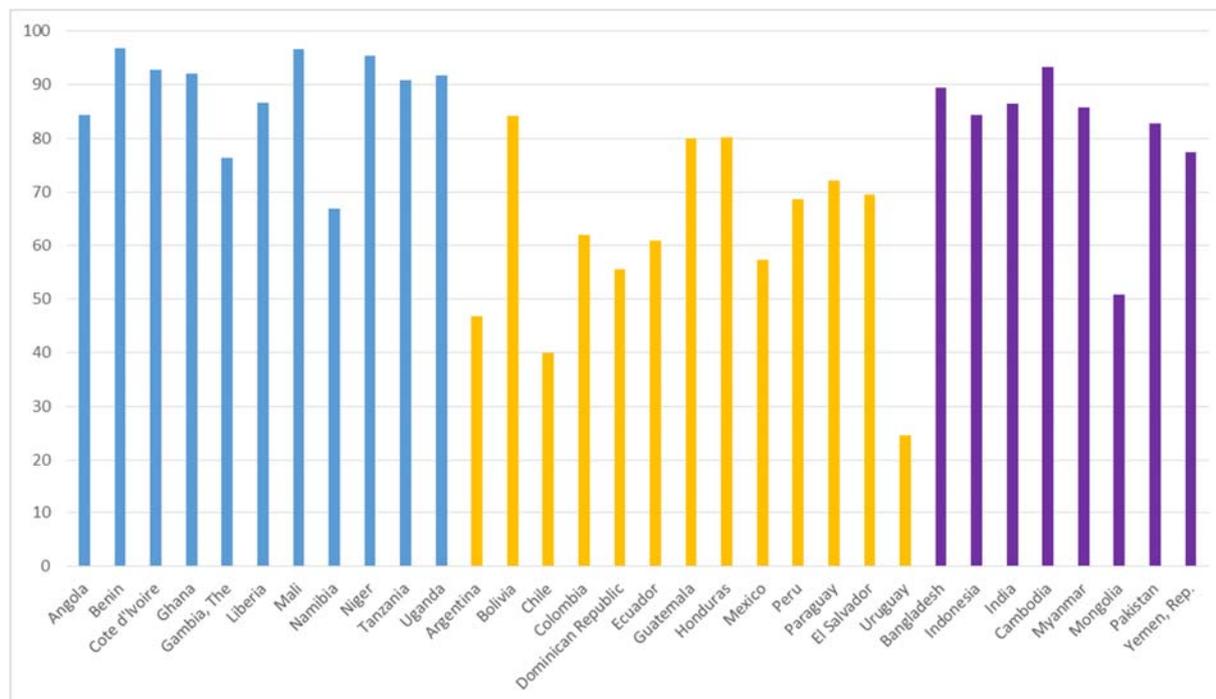
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## 1. Introduction

Labor markets in developing countries are characterized by high levels of informality. Figure 1 displays shares of informal employment (as a percentage of non-agricultural employment) in a series of countries in Sub-Saharan Africa (left hand side, blue color), in Latin America (center, orange color), and Asia (right hand side, purple color). The figure illustrates that levels of informality differ somewhat between major regions: in Latin America, these shares are in the range of 24.5 (Uruguay, 2016) and 84 per cent (Bolivia, 2015), and thus lower than in Sub-Saharan Africa – where the majority of countries have shares higher than 70 per cent – and Asia. Notwithstanding these regional differences and the general downward trend in informality since the early 2000s (e.g. Maurizio and Vázquez 2017), however, the figure shows that overall levels of informal employment remain high across the developing world.

Figure 1. Informal employment as % of non-agricultural employment, latest available year



Note: World Bank data. Shares reported are from the latest available year 2011-2016, respectively.

In order to address this persistent challenge, a multitude of policies and programs have therefore been implemented in many countries with the aim to increase the formalization of firms or workers, or both. First, among initiatives to formalize businesses are, for instance, the implementation of one-stop shops for business registration and the simplification of payroll taxes and social security contributions (e.g. Bruhn 2011 and Fajnzylber et al. 2011 for Mexico). Other approaches concern information interventions, e.g. information campaigns that explicate the step-by-step procedures and potential benefits of business registration (De Giorgi and Rahman 2013 for Bangladesh). Also programs that reduce the costs of business registration are considered and put into practice (Alcázar and Jaramillo 2016 for Peru), as are financial mechanisms in which a bonus payment is given to firms who are willing to register (de Mel et al. 2013 for Sri Lanka). Finally, a potential alternative to incentive-based approaches are interventions that enforce business formalization (e.g. De Giorgi et al. 2017 for Bangladesh).

The second type of approaches targets the formalization of labor, such as the registration of workers. This includes e.g. tax reduction and bureaucracy simplification policies such as SIMPLES in Brazil (Monteiro and Assuncao 2012). Other cost-reducing approaches include reductions in payroll taxes (e.g. Bernal et al. 2015 for Colombia) or the simplification of labor registration (e.g. Ronconi and Colina 2011 for Argentina). Finally, as in the case of targeting businesses, also when targeting workers the enforcement of formalization legislation is a policy option (Pignatti 2017 for Colombia). Clearly, several of the approaches mentioned here and in the above paragraph are potentially combinable into a multi-treatment approach.

Given the policy relevance of labor market informality and the large spectrum of interventions aiming at increasing formality, the empirical evaluation of these interventions is of key interest to policy makers, to learn about the effectiveness of formalization initiatives. Some of the earlier evidence is reviewed in Bruhn and McKenzie (2014), who find, for instance, that approaches that comprise the ease of formalization alone will not induce most informal firms to become formal, while increased enforcement of rules can increase formality.

In this paper we review the evidence on the effects of formalization interventions in developing countries in a quantitative way. That is, we compile a (meta-) database of impact evaluations of such formalization policies and programs and then empirically analyze the

patterns of intervention effectiveness by e.g. intervention type and outcome considered. The next section delineates the compilation of the database, while section 3 presents a descriptive statistical analysis. In section 4 we delineate and implement the meta-analytical approach to investigate correlates of the effectiveness of formalization interventions. Section 5 concludes.

## **2. A database of evaluations of formalization interventions**

The objective of the data compilation is to construct a meta-data base of impact evaluations and quantitative assessments of formalization interventions worldwide, focusing on developing countries and emerging economies. This process proceeds in essentially three steps: 1) The first step is to search for relevant studies; 2) the second step is to verify the inclusion criteria to arrive at the final set of relevant studies; and 3) the third step is to systematically extract information from the primary studies and code it into the meta data set. These steps are explained briefly in this section; full details of the search and coding process are given in the appendix..

The first step uses a broad set of search terms (including e.g. terms such as "formalize", "formalization", "registration simplification", "labor inspection", etc.) and applies them to a title and abstract search in a series of websites and research databases in which relevant studies would be contained (such as e.g. the Social Science Research Network SSRN, IDEAS, Google Scholar, the 3ie Repository of Published Impact Evaluation studies, etc.). The studies identified through this first step are then given a full-text assessment in the second step, in which the following main inclusion criteria are considered:

- Study available in English.
- Empirical studies with a quantitative assessment of the effect or impact of a formalization program or policy using some version of a selection correction (counterfactual impact assessment, i.e. estimation of a causal treatment effect). In general, this can include studies based on experimental designs (Randomized Controlled Trials), quasi-experimental or non-experimental methods.

- Distinguishable estimate of the effect or impact of the formalization program or policy, with an indication of the statistical significance of the estimate.
- Distinguishable formalization program or policy that can be categorized into one of the five intervention types specified below.
- Studies that assess the impact on one of the six outcome variables specified below.
- In line with the objectives of the review (see above), and because in general symmetry of effects cannot be assumed, only studies with a "switch-on" type of intervention that target *improved* formalization outcomes are included. That is, for instance, a study that looks at how tax increases may lead to a reduction in formal employment would not be in-scope.
- Search hits of studies focusing on the "hidden economy" or "shadow economy" are not in-scope.

All studies fulfilling these criteria are then used to extract information into the meta data base. In our case, 28 primary studies were identified by the search process that also fulfilled the inclusion criteria. The main information to be extracted from the primary studies concerns, first, the intervention analyzed, secondly, the outcome used to measure program effectiveness, and thirdly the estimate of the intervention impact. We will discuss these in turn.

First, to adequately distinguish between different forms of formalization interventions, we identify five main types classifiable as follows; i) information intervention, ii) simplification / registration, iii) tax incentive, iv) financial incentive, and v) labor inspection. Information interventions (i) tend to either inform firms and / or workers about the benefits of formalization or they emphasize the legal obligation to register. Studies in our data that analyze this intervention type primarily stem from experimental evidence. The second intervention type either (ii) simplifies the registration process or supports firms and workers in doing so. With the exception of two pilot programs and one experiment, all simplification interventions are policies, i.e. implemented at scale.

Intervention types (iii) and (iv) both make it financially more attractive (i.e. less costly) to register, but differ in one important dimension; tax incentives reduce the tax burden firms or workers face and thereby incentivize them to become formal. In our data base, these policies

are mostly implemented with the explicit goal to reduce informality. Financial incentives on the other hand offer costless business registration or hand out a reward payment explicitly for this purpose. The offers are typically time-limited and introduced in experimental settings.

Whereas the financial incentive intervention types offer a “carrot” treatment, (v) labor inspections are designed as “sticks”. Although rates of informality are often high in developing countries (cf. Figure 1), operating without a license or without having workers registered frequently is illegal. Brazil and Colombia, for instance, both increased the number of labor inspectors to combat informality, and two other studies in our data test the effectiveness of inspections in experimental settings. Tax incentive and labor inspection are mostly single interventions, whereas the information and simplification interventions and financial incentives are usually combined with one or two other types.

Second, to measure the effects of these interventions, we consider six outcomes; i) number of registered firms, ii) number of formal jobs, iii) wages, iv) firm profitability, v) tax revenue, and vi) investment. More than 80 percent of observations in our data stem from the first two categories. The first outcome looks at the number of registered firms or the probability of a set of firms to register. The second outcome looks at the same outcome at the level of the worker and considers the number of formal jobs, individual registration or the share of formally employed workers in an economy.

When examining the impact on wages we seek to identify whether the formalization interventions have led to increased wages for workers. This could be the case if, e.g. employing registered workers has become cheaper for firms (intervention type iii) and iv)) which increases workers’ bargaining power, or if being registered leads to increased firm performance. The latter point is considered by the outcomes iv) and vi), which both look at firm outcomes. A reason why formalization interventions have become increasingly popular is that it is widely believed that formality can improve firm performance, e.g. by giving firms access to credit markets and by making it easier for firms to grow.<sup>2</sup> A major goal of governments aiming at increasing formality is to boost tax revenue (outcome v). Large informal economies are a main

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<sup>2</sup> Evidence suggests that firms may stay inefficiently small to avoid being obliged to register and pay taxes (e.g. Bruhn and Loeprick 2016).

reason why many developing countries have a low tax base. By making it cheaper for firms or workers to become formal, it is hoped that the increase in formality can increase tax revenue despite reducing marginal tax rates.

Third, and most importantly, the coding process needs to extract a measure of the program effect, in order to be correlated in the empirical analysis with other variables from the primary studies to investigate whether program effectiveness shows systematic features by program characteristics. As a first and main measure, we use the trinomial indicator of sign and statistical significance (convention: at the 5% level) of the estimated intervention effect or impact: (i) negative and statistically significant, (ii) not statistically different from zero, and (iii) positive and statistically significant.

Ideally, in a second step, one would like to extract a measure of the size of the estimated impact, i.e. the coefficient of the estimated treatment effect (see e.g. Card et al. 2017). Doing this in a comparable way in the given context of formalization interventions, however, is not possible because of the heterogeneity of the outcomes considered in the primary studies. Notwithstanding this potential limitation, whenever a study provides information on the mean outcome of the control group, we quantitatively relate this to the estimated coefficient in order to code the "per cent impact of the intervention". Note that whereas this measure cannot be interpreted in units of specific outcomes, it has the advantage of being dimensionless and thus comparable across heterogeneous outcomes.

The coding process, in addition, includes several more variables in three main groups characterizing (a) the study, (b) the intervention, and (c) the empirical analysis (the following is a shortened list with the most relevant variables; the full list is explained in Jessen and Kluge 2017).

(a) Study characteristics:

- Country
- Authors; Title; Publication status (year; journal, if applicable)

(b) Intervention characteristics:

- Target of the formalization intervention: firms, workers, or both.
- Scope of the intervention: program or policy.

— Year of the policy change or implementation of intervention (if applicable).

(c) Empirical analysis:

- Time horizon of the study: start and end
- Unit of observation: (i) firm, (ii) worker, (iii) linked, (iv) other
- Data source and size of the estimation sample
- Time horizon of the outcome measurement (in months since reform date / start of the intervention)
- Identification strategy and empirical method

When a study reports estimated impacts for (a) separate interventions, (b) separate outcomes, (c) separate groups of firms or workers, or (d) at separate time horizons, then these estimates are coded separately; that is, one study typically yields more than one observation in the meta data. Overall, it was possible to extract 121 impact estimates from the 28 primary studies. The trinomial measure of sign/significance is available for all estimates, and the per cent impact is available for 79 estimates, i.e. for about two thirds of the sample.

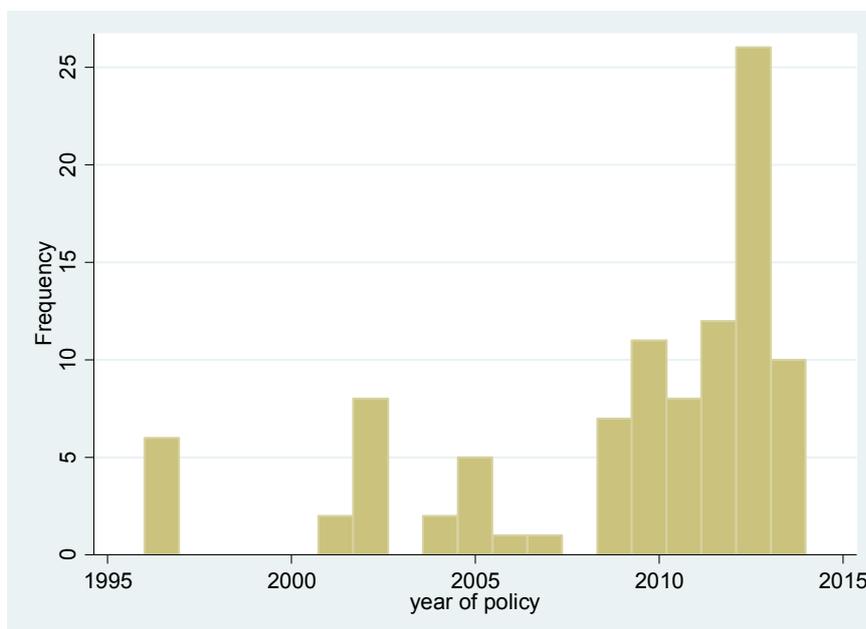
Table 1. Distribution of countries in meta data on formalization interventions

Country	Observations		Studies	
	Freq. (1)	Percent (2)	Freq. (3)	Percent (4)
Argentina	4	3.31	1	3.57
Bangladesh	2	1.65	2	7.14
Benin	3	2.48	1	3.57
Brazil	26	21.49	9	32.14
Colombia	36	29.75	5	17.86
Georgia	10	8.26	1	3.57
Malawi	12	9.92	1	3.57
Mexico	8	6.61	3	10.71
Peru	9	7.44	2	7.14
Russia	2	1.65	1	3.57
Sri Lanka	5	4.13	1	3.57
Turkey	4	3.31	1	3.57
	121		28	

Table 1 presents an overview of the countries in the data. It can be seen that a set of countries with specific reforms, some of which were analyzed in more than one paper, is prominently represented in the data (e.g. Brazil with 26 estimates from 9 studies, and Colombia with 36 estimates from 5 studies). Overall, the majority of analyses of formalization policies and programs originates in countries in Latin America (83 impact estimates = 69%), but still around one third of estimates (38) are from non-LAC countries. The overall number of countries in the sample (12) is not very large, which indicates that the use of these policies and/or their quantitative analysis is not very widespread.

Figure 1 shows the distribution of the years in which the respective reform or intervention was implemented. The distribution indicates that these reforms / interventions analyzed are very recent: more than two-thirds of the impact estimates for which this information was available (75 out of 108, i.e. 69.4%) are from interventions implemented in 2010 or later.

Figure 1. Year in which the formalization intervention or reform was implemented



### 3. Empirical analysis (i) – descriptive analysis

This section presents a descriptive statistical analysis of the main patterns in the meta data. Table 2 gives an overview of the features of the impact evaluations of formalization interventions. Looking at the "intervention type", estimates of tax incentive interventions represent the largest share in the data (54 estimates, 45%), followed by simplification/registration interventions (36%) and information approaches (22%). Financial incentives also cover more than one fifth in the data (21%), and 16 estimates describe impacts of labor inspection interventions (13%).

As the next panel indicates, the large majority of estimates originates from single-intervention programs and evaluations (87 estimates, or 72%). 18% of estimates are from interventions that combine two different approaches, and 10% of estimates are from interventions that combine three. That is, more than one quarter of the sample covers multi-approach interventions.

Looking at the "formalization target" there is an almost fifty-fifty distribution between firms and workers in being targeted by the formalization intervention (50% and 45%, respectively). A residual 5% of impact estimates is from interventions that target both. In terms of the intervention scope, 84 of the impact estimates (69%) refer to „policy“-type interventions, while 37 (31%) refer to „program“-type interventions. This relation is identical when looking at the study level: 8 of the 28 studies (29%) analyze „programs“, while 20 studies (71%) analyze „policies“. That is, the typical primary study analyzing a program produces on average the same number of impact estimates as the typical primary study analyzing a policy.

Finally, and perhaps unsurprisingly, in terms of the outcomes the majority of impact estimates investigate either impacts of formalization interventions on (1) the number of registered firms / firms' registration probability, or (2) the number of formal jobs / formal employment / worker registration, with around 40% in the sample each. Wage outcomes are analyzed in just under 10% of cases, while formalization impacts on firm profitability, tax revenue, and investment remain the exception.

Table 2. Features of impact evaluations of formalization interventions

	Freq. (1)	Percent (2)
Number of estimates	121	
Number of studies	28	
<u>Intervention type</u>		
Information intervention	27	22.3
Simplification / registration	44	36.4
Tax incentives	54	44.6
Financial incentives	26	21.5
Labor inspection	16	13.2
<u>Number of interventions</u>		
Single intervention	87	71.9
Two combined	22	18.2
Three combined	12	9.9
<u>Formalization target</u>		
Firm	61	50.4
Labor	54	44.6
Both	6	5.0
<u>Formalization scope</u>		
Program	37	30.6
Policy	84	69.4
<u>Outcome</u>		
Registered firms*	47	38.8
Formal jobs*	51	42.1
Wages	11	9.1
Firm Profitability	3	2.5
Tax Revenue	7	5.8
Investment	2	1.7

\* Registered firms denote the number of formally registered firms or registration probability. Formal jobs denote number of formal jobs, worker registration or probability to register. Evidently it varies from country to country what precisely "registration" entails.

In Table 3 we begin investigating patterns of effectiveness by looking at sign and significance of the estimates. The table shows that the (slight) majority of impact estimates are positive and statistically significant (52%). At the same time, only 6 impact estimates (5%) are

negative and statistically significant; this means that more than 40% of impact estimates (52) are not statistically different from zero.

Table 3. Distribution of estimated intervention impacts by sign and significance

	Freq. (1)	Percent (2)
Negative and statistically significant	6	5
Insignificant	52	43
Positive and statistically significant	63	52

Note: statistical significance is determined on a 5 percent significance level

Figure 3. Sign and significance of estimated intervention impacts by intervention type

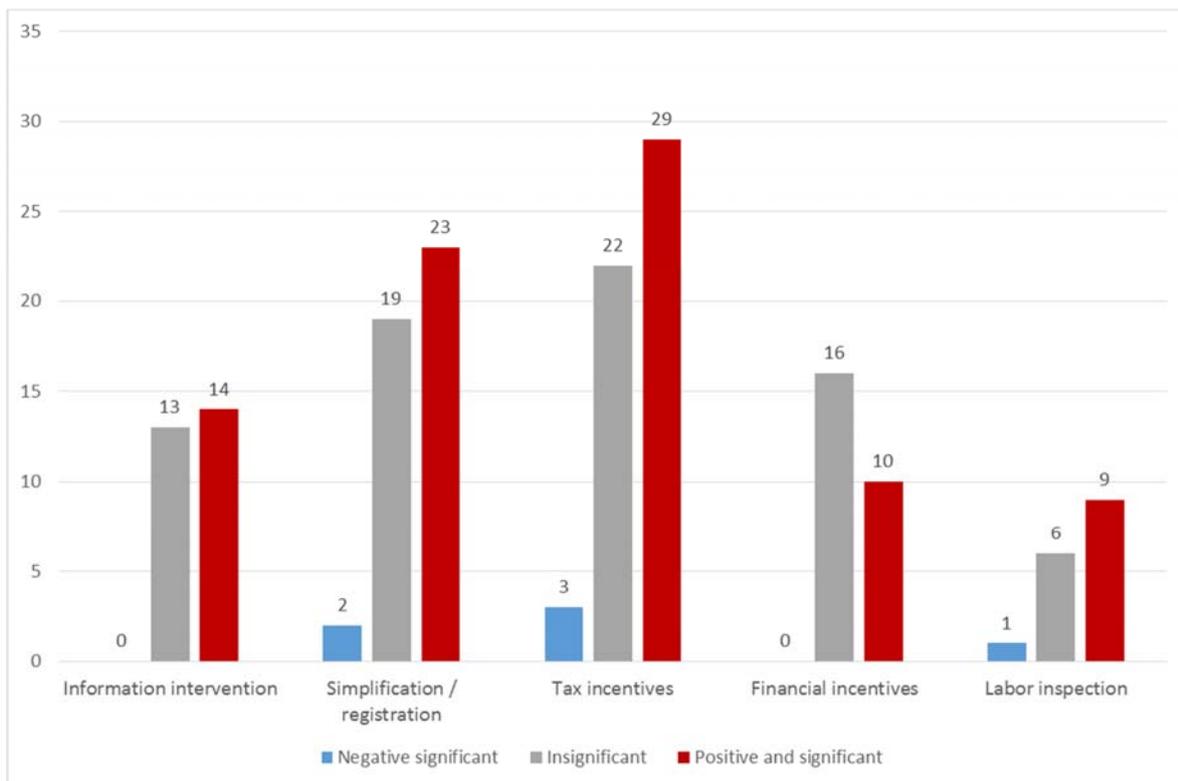
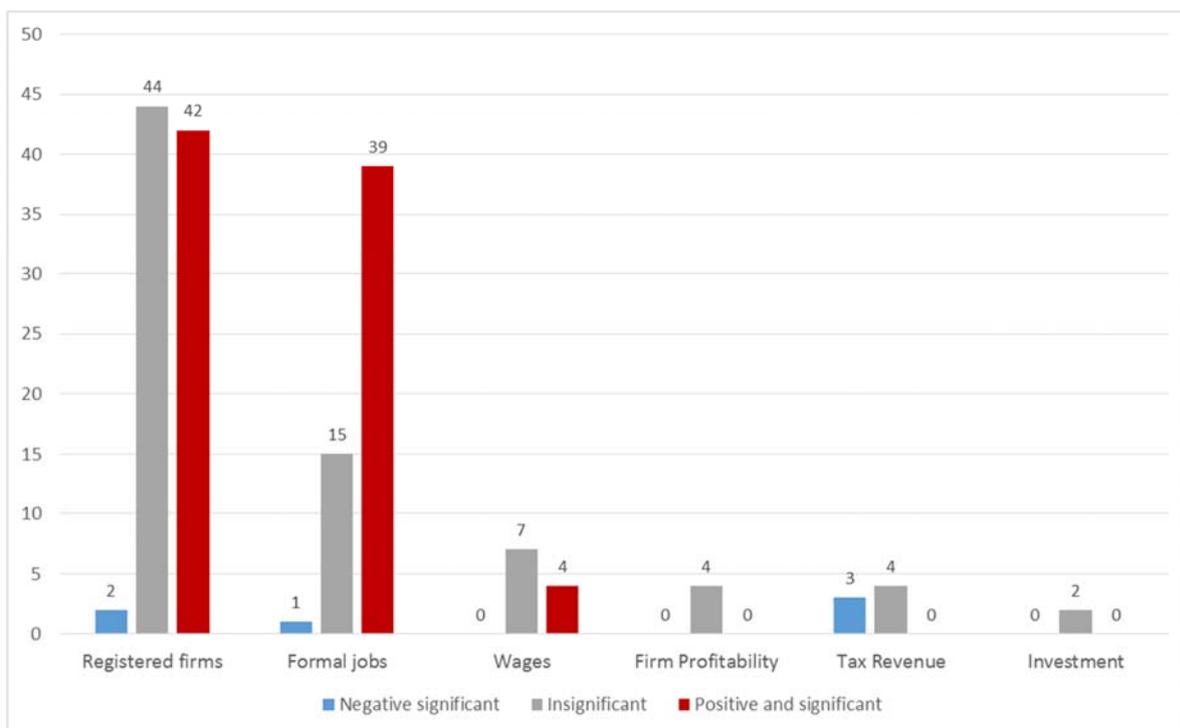


Figure 3 stratifies the distribution of program estimates that are negative significant, insignificant, or positive significant by intervention type. The distribution shows that for all intervention types except "financial incentives" the share of positive significant estimates is

larger than for insignificant estimates, indicating that these programs, on average, display less positive results. The second main finding of the graph is that there is no pronounced pattern by intervention type; the relative share of positive significant impacts is highest for labor inspection (56%), followed by tax incentives (54%), simplification/ registration (53%) and information intervention (52%).

Figure 4 displays sign and significance of intervention impacts by outcome type considered in the primary study. Different from the intervention type distribution in Figure 3 the patterns by outcome are rather pronounced. First, the shares of positive significant impacts differ strongly: impacts on the number of formal jobs and worker registration have by far the highest probability of showing positive impacts (73%). For the second main outcome, firm registration, this probability of a positive impact is still 47%. For wages it is 37%, and the number of observations is quite small. It is even smaller for the remaining three outcomes – firm profitability, tax revenue, and investment – but it is nonetheless worth noting that none of the estimated impacts for these outcomes is positive and statistically significant.

Figure 4. Sign and significance of estimated intervention impacts by outcome measure



In addition to these patterns by sign and significance, in Figures 5 to 8 we investigate results by the estimated percent impacts of the formalization interventions. First, Figure 5 plots the distribution of the 79 percent impacts, also indicating which of these relate to a negative and statistically significant (blue color), insignificant (grey), or positive and statistically significant (red) point estimate.

Several of the percent impact estimates are very large, attaining values of more than 100 percent impact (13 out of 79). These originate in the field experiments in which firms are offered/exposed to several treatment arms (e.g. de Mel et al. 2013). Given the design of these studies, the mean value of the outcome in the control group will be relatively low compared to the treatment arms, hence generating very large percent impacts (to be clear, this is not a shortcoming of these studies at all, but instead a shortcoming of the per cent impact measure). To illustrate this, consider the study from de Mel et al. (2013) just mentioned: in the time period of analysis two out of 105 control firms registered (0.019 registration probability), whereas in one of the treatment groups 30 firms did. Controlling for covariates, the treatment on the treated point estimate on the registration probability is 0.471, which implies an estimated percent impact of 2,477 percent (this is the largest in our sample). In order to make the presentation of our findings accessible in the figures, we set all percent impacts larger than 100 percent to 100 percent: this is the horizontal line of impact estimates at "100" that can be seen in the graph.

Figure 6 distinguishes the percent impacts by outcome considered in the evaluation study. In line with the explanation in the previous paragraph that the very large percent impacts originate from the experimental designs testing several formalization treatments for firms to register, these impacts all concern the outcome "firm registration" (green color). It is also visible in Figure 6 that this firm registration outcome is spread across the full range of impact sizes, ranging down to the lowest estimated percent impact in the data (-72%). This broad spread of impact sizes for this outcome – with many values being either negative or positive and large – then translates into an overall moderate probability of a positive significant impact on firm registration found in Figure 4 (47%).

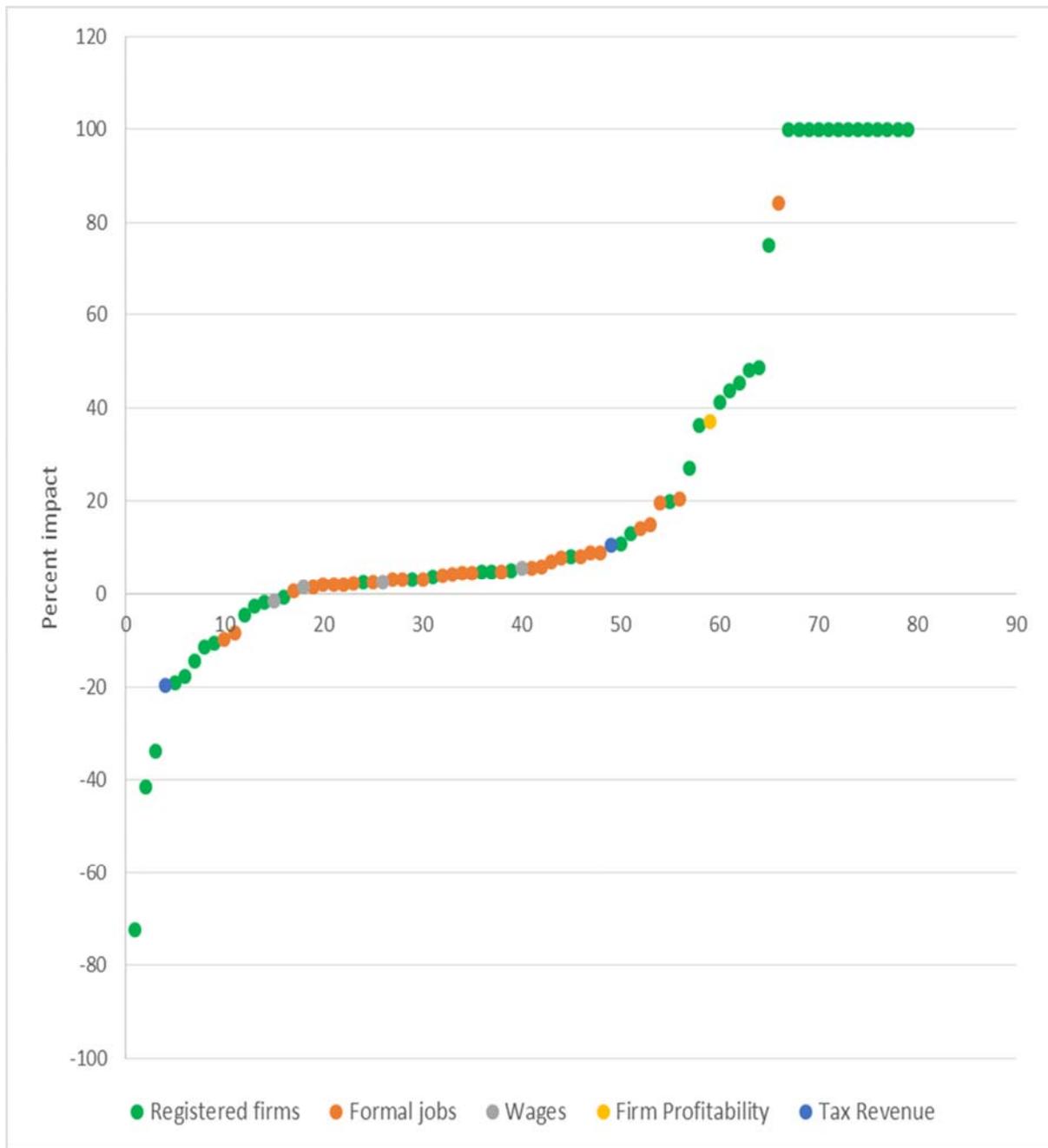
At the same time, also recalling from Figure 4 the high probability of a positive significant impact on the outcome "formal jobs" (73%), note that Figure 6 shows that the impact sizes on formal jobs (orange color) vary much less, and almost all estimates cluster in the bracket from 0 to 20 per cent impact. The per cent impacts on wages (grey color) are also rather small, but for this outcome – and for firm profitability and tax revenue – the number of observations is too small to draw any conclusions.

Figure 7 displays the percent impact distribution by intervention type, plotting multiple dots if a percent estimate originates in an intervention combining more than one intervention type. Figure 3 above showed little indication of a pattern of formalization effectiveness by program type, and this finding is confirmed by Figure 7 showing a relatively large spread for all intervention types. There might be a slight clustering of the "labor inspection" interventions (blue color) in the range of "smaller" impacts of 0 to 20 percent, but the pattern is not conclusive and indicative at best. For the other intervention types, in particular information interventions (green) and simplification/registration interventions (orange), the full range of percent impacts can be seen.

Finally, Figure 8 makes the distinction between percent impact estimates originating from the evaluation of a program (i.e. small-scale, singular or targeted intervention, in blue color) and a policy (i.e. implemented at scale, in orange color). The figure indicates that estimated impact sizes from evaluations of "programs" are spread out much more, and in fact tend to be either negative or positive and large. Very few of the point estimates for "programs" are in the moderate range of 0 to 20 percent impact. For the percent impacts of evaluations of "policies" this pattern is reversed: the large majority of the estimates cluster in that range of moderately positive impact sizes, while only few of the percent impacts of the evaluations of "policies" are negative or positive and larger than 20 percent.

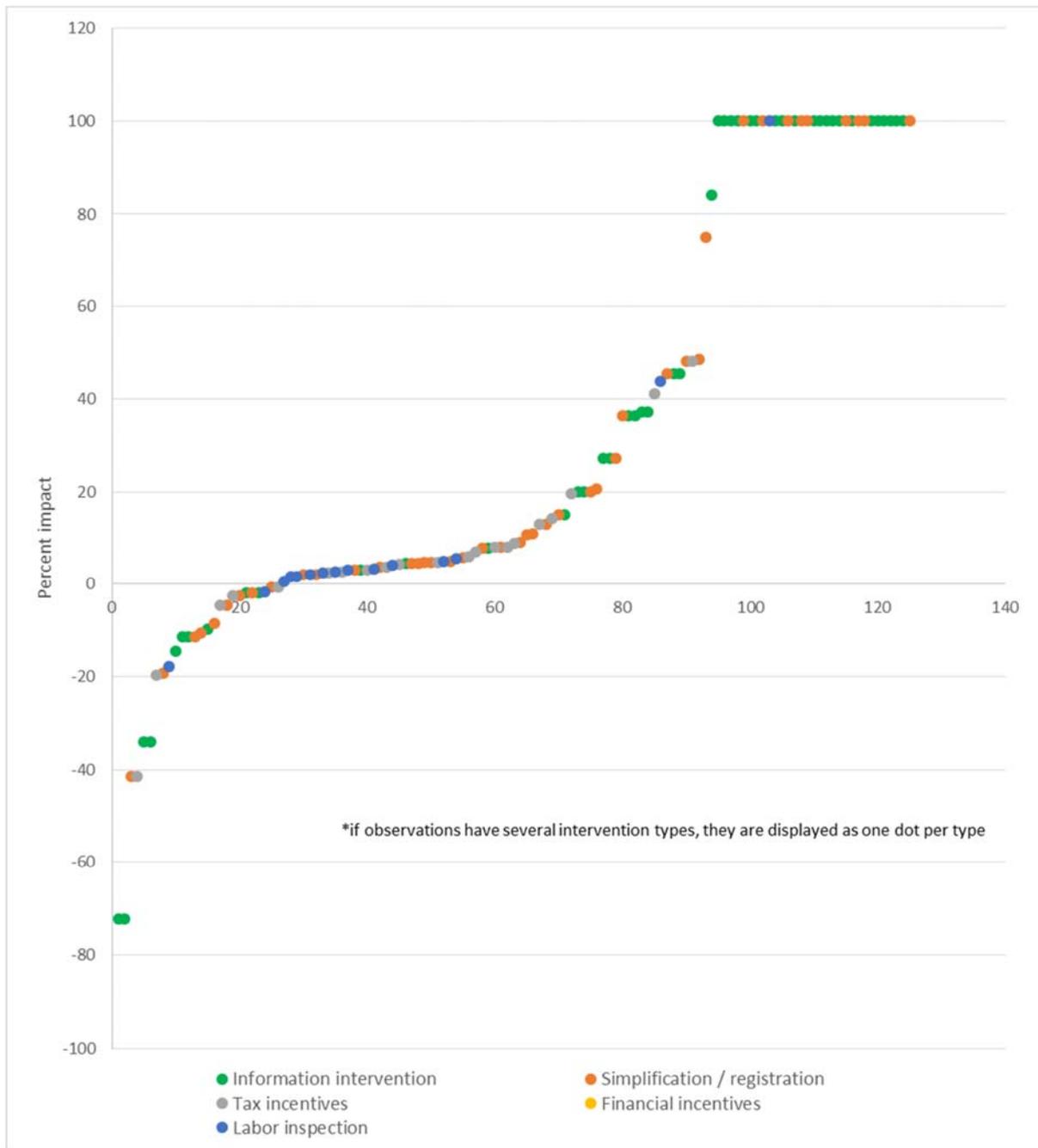


Figure 6. Percent impacts of formalization interventions by outcome measure



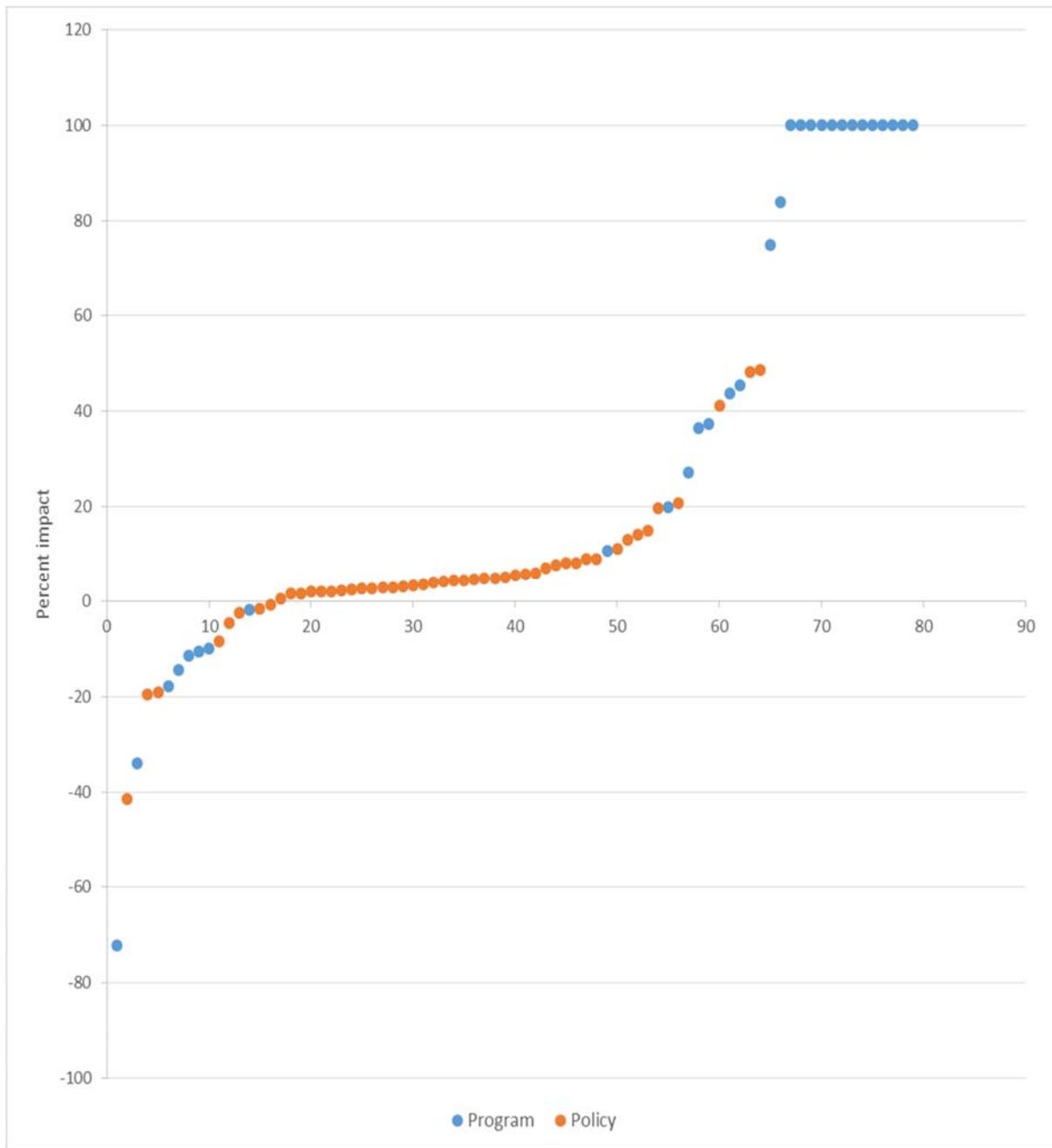
Note: 13 estimated percent impacts larger than 100 percent are set to 100 in the graph for better illustration.

Figure 7. Percent impacts of formalization interventions by intervention type



Note: 13 estimated percent impacts larger than 100 percent are set to 100 in the graph for better illustration.

Figure 8. Percent impacts of formalization interventions by intervention scope



Note: 13 estimated percent impacts larger than 100 percent are set to 100 in the graph for better illustration.

## 4. Empirical analysis (ii) – Meta analysis

### 4.1 Conceptual framework

The multivariate analysis follows the conceptual approach outlined in the meta analysis of active labor market policies outlined in Card et al. (2017). Specifically, consider a formalization intervention that models an outcome  $y$  observed for members of both a treatment group and a comparison group. Let  $b$  represent the estimated impact of the intervention on the outcomes of the treated units from a given evaluation design, and let  $\beta$  represent the probability limit of  $b$  (i.e., the estimate that would be obtained if the sample size for the evaluation were infinite). Under standard conditions the estimate  $b$  will be approximately normally distributed with mean  $\beta$  and some level of precision  $P$  that depends on both the sample size for the evaluation and the design features of the study. This leads to:

$$b = \beta + P^{-1/2} z, \tag{1}$$

where  $z$  is a realization from a distribution that will be close to  $N(0,1)$  if the sample size is large enough. The term  $P^{-1/2}z$  has the interpretation of the realized sampling error that is incorporated in  $b$ . In the next step, assume that the limiting intervention effect associated with a given study ( $\beta$ ) can be decomposed as:

$$\beta = X\alpha + \varepsilon, \tag{2}$$

where  $\alpha$  is a vector of coefficients and  $X$  captures the observed sources of heterogeneity in  $\beta$ , arising for example from differences in the type of intervention, characteristics of target group or contextual factors. The term  $\varepsilon$  represents fundamental heterogeneity in the limiting intervention effect arising from the particular way it was implemented, specific features of the intervention or its target group, or the nature of the (labor) market environment. Equations (1) and (2) lead to a model for the observed intervention effect estimates of the form:

$$b = X\alpha + u , \tag{3}$$

where the error  $u = \varepsilon + P^{-1/2}z$  includes both the sampling error in the estimate  $b$  and the unobserved determinants of the limiting intervention effect for a given study.

Card et al. (2017) propose the use of simple regression models based on equation (3) to analyze the labor market intervention effects on the relevant outcomes available in the metasample. The interpretation of these models in our case is that they provide descriptive summaries of the variation in average intervention effects due to differences in the observed characteristics of a given formalization intervention and target group, and contextual factors (including methodological study features). Recognizing the structure of the error component in (3), Card et al. (2017) prefer OLS estimation, which weights each estimated intervention effect equally, rather than the precision-weighted estimation, which would be efficient under the assumption that  $\varepsilon=0$ . As they point out, in contrast to “classical” meta-analysis settings where each estimate is based on a clinical trial of the same drug, also in our case the variation in  $\varepsilon$  could be particularly large, reflecting the wide range of factors that can potentially influence a formalization intervention to be more or less successful.

Following this methodological approach, and extracting for each estimate information related to whether it was “statistically significant negative”, “statistically significant positive”, or “not statistically significant from zero”, the analysis estimates an (unweighted) ordered probit (OP) model for this 3-way classification of intervention effects. Note that the t-statistic associated with the estimated impact  $b$  is the ratio of the estimate to the square root of its estimated sampling variance (which is the inverse of its estimated precision). Using equation (3), this leads to (Card et al. 2017):

$$\begin{aligned} t &= P^{1/2} b \\ &= P^{1/2} X\alpha + z + P^{1/2} \varepsilon \end{aligned}$$

If the precision  $P$  of the estimated intervention effects is constant across studies and there are no unobserved determinants of the limiting intervention effect (i.e.,  $\varepsilon=0$ ), the t-statistic will be normally distributed with mean  $X\alpha'$  where  $\alpha' = P^{1/2} \alpha$ . That is, the coefficients from an OP model for whether the t statistic is less than -2, between -2 and 2, or greater than 2 (i.e., the sign and significance of the estimated intervention effects) will be strictly proportional to the coefficients obtained from a regression model of the corresponding estimated effect sizes.

#### **4.2 Estimation results**

Table 4 reports findings from an ordered probit regression, in which the sign and significance of the estimated impact is correlated with a series of explanatory variables, in blockwise fashion.

Panel (a) indicates that there is no statistically significant pattern by intervention type, confirming the findings from the descriptive analysis in section 3. Moreover, the coefficients are all relatively small in size, indicating that indeed the intervention type per se is not a main predictor of whether a formalization intervention works or not.

Looking at the study outcomes in panel (b), on the other hand, we find again that firm registration is (marginally) more likely to be affected in a positive way, relative to other outcomes, whereas formal jobs – the probability of worker registration – is the outcome that is most strongly affected positively by formalization interventions.

Panel (c) looks at features of the data, but does not indicate any strong patterns. Panel (d) shows that research designs based on either experimental or quasi-experimental designs are more likely to be correlated with positive impacts; however, the number of studies with non-experimental designs is small in the sample. Finally, larger samples are marginally linked with a higher probability of obtaining a statistically significant positive impact estimate.

In Table 5 we expand this analysis to full multivariate specifications. The main patterns are maintained, as shown in particular in column (4): first, the intervention type is not a strong determinant of intervention effectiveness; second, formal jobs=worker registration is the outcome most strongly affected in a positive way; third, larger sample sizes are associated with a higher probability of a positive significant impact estimate; fourth, other factors – including

Table 4. Meta analysis models of sign/significance of estimated program effect: blockwise correlations

	(1)	(2)	(3)	(4)
<u>(a) Intervention type (base=financial incentive)</u>				
Simplification/registration	0.081 (.321)			
Information	0.275 (.421)			
Tax incentive	0.247 (.452)			
Labor inspection	0.299 (.507)			
<u>(b) Outcome and scope (base= wage, tax revenue, other; policy)</u>				
Registered firms		0.686 (.342)		
Formal jobs		1.232 (.411)		
Intervention=program		-0.136 (.316)		
<u>(c) Data (base=obs.unit: workers; data: survey)</u>				
Observation unit: firm			-0.699 (.429)	-0.133 (.539)
Observation unit: firm and workers linked			0.7 (.424)	0.853 (.534)
Data: Administrative			0 (.424)	-0.095 (.413)
Data: Admin plus survey			0.281 (.409)	0.368 (.518)
<u>(d) Methodology (base: non-experimental design)</u>				
Experimental design			-4.7 (.3)	-4.665 (.31)
Quasi-experimental design			-5.064 (.44)	-4.953 (.494)
Square root of sample size				0.001 (.)
Time horizon for effect measurement (months)				0.022 (.015)

Note: Table entries are coefficients from an ordered probit specification, in which the dependent variable takes on the values of +1, 0, and -1 for an estimated program effect being positive statistical significant, insignificant, and negative statistical significant, respectively. Standard errors in (parentheses) are clustered at the study level.

Table 5. Meta analysis models of sign/significance of estimated program effect: full specifications

	(1)	(2)	(3)	(4)
<u>(a) Intervention type (base=financial incentive)</u>				
Simplification/registration	-0.288 (.306)	0.364 (.544)	0.697 (.466)	-0.161 (1.148)
Information	0.369 (.473)	-0.119 (.554)	-0.595 (.619)	-0.646 (.889)
Tax incentive	-0.216 (.62)	0.347 (.777)	-0.513 (.868)	-0.523 (1.148)
Labor inspection	-0.236 (.601)	0.219 (.765)	-0.076 (.804)	0.317 (1.005)
<u>(b) Outcome and scope (base= wage, tax revenue, other; policy)</u>				
Registered firms	0.718 (.402)	1.124 (.442)	1.479 (.475)	1.498 (.526)
Formal jobs	1.198 (.392)	1.617 (.475)	1.508 (.44)	1.188 (.437)
Intervention=program	-0.474 (.539)	-2.017 (.575)	-2.775 (.862)	-2.848 (1.033)
<u>(c) Data (base=obs.unit: workers; data: survey)</u>				
Observation unit: firm		-0.609 (.584)	-0.83 (.567)	-0.178 (.745)
Observation unit: firm and workers linked		0.426 (.507)	0.3 (.537)	0.189 (.654)
Data: Administrative		0.943 (.489)	1.058 (.569)	1.021 (.586)
Data: Admin plus survey		-0.594 (.66)	-0.657 (.594)	0.4 (.889)
<u>(d) Methodology (base: non-experimental design)</u>				
Experimental design		-4.883 (.64)	-4.223 (.65)	-5.013 (1.255)
Quasi-experimental design		-8.8 (1.25)	-8.314 (1.288)	-6.126 (2.006)
Square root of sample size		0.001 (.)	0.000 (.)	0.000 (.)
Time horizon for effect measurement (months)				
<u>(e) Main countries in data</u>				
Brazil			-0.699 (.336)	-1.55 (.798)
Colombia			0.578 (.688)	-0.446 (.92)
Mexico			-1.472 (1.01)	-3.926 (2.179)
<u>(f) Contextual factors</u>				
Unemployment rate				-0.275 (.16)
GDP growth				-0.081 (.152)
Poverty index				-0.003 (.024)

Note: see Table 3.

contextual variables such as unemployment rate and GDP growth – do not seem to explain strongly the variation in intervention effectiveness. Fifth and finally, we find that evaluations of interventions with a larger scope (i.e. "policies") are significantly more likely to report positive impacts than evaluations of interventions with a more limited scope ("programs").

## 5. Conclusion

Against the background of high levels of informality in many labor markets in developing countries and emerging economies this paper has analyzed patterns of the effectiveness of formalization interventions that aim at alleviating this labor market policy challenge. The analysis has proceeded in a systematic and quantitative way: we first compile a meta data base of impact evaluations and quantitative assessments of formalization policies, and then investigate patterns of the estimated impacts in the data, both in a descriptive and multivariate way.

The key empirical challenge is to correlate intervention effectiveness with intervention characteristics. In particular, we consider two measures of program effectiveness, the sign and significance of the estimated impact, and the size of the estimated impact, as measured by the percent change in the outcome in the treatment group relative to the control group average. The main explanatory variables considered are intervention type – classified into five categories: information intervention, simplification/registration, tax incentives, financial incentives, labor inspection – and outcome variable. The latter comprises firm registration and labor registration (the two main groups), and also wages, firm profitability, tax revenue and investment.

Several interesting patterns are found in the data. First, on the basis of this quantitative analysis there is little indication that the intervention type is a strong determinant of the effectiveness of formalization interventions. Both measures of intervention effectiveness – sign/significance of the estimated impact, and percent size – do not vary systematically with the intervention type. There is some hint that "financial incentive" type of interventions may have a

somewhat smaller probability of displaying a positive significant impact, but this finding is tentative in the descriptive analysis and not borne out by the meta regressions.

Second, visible patterns appear by type of outcome measure. Estimates on the outcome "formal jobs / labor registration" – i.e. for interventions targeting workers – display a much higher probability of a positive and significant impact than estimates on the other outcomes, in particular the second main outcome considered in the evaluations, "firm registration". This is an important finding that may point to worker registration being a key avenue to labor market formalization, and potentially more promising than interventions that specifically target other features of formalization.

Third, when also taking into account the size of estimated impact (in percent terms), this pattern by outcome type shows that, while estimates on "formal jobs / labor registration" have a high probability of being positive significant, they cluster in the "moderate" range of impact sizes, between 0 to 20 percent. Impacts on "firm registration", on the other hand, vary widely in size and range from negative to positive and very large.

Fourth, we find that impact sizes of the evaluations of formalization "programs" – i.e. small-scale, singular, targeted interventions – are larger in size and vary widely, whereas impact sizes of the evaluations of formalization "policies" implemented at scale are moderate in size and vary less. At the same time, and perhaps more importantly, evaluations of "policies" are significantly more likely to report positive outcomes than evaluations of "programs". This implies that while effect sizes at scale may be smaller than those achievable by singular programs, formalization policies at scale have a generally higher probability to be effective.

## References

Alcázar, L. and M. Jaramillo (2016), *The Impact of Formality on Microenterprise Performance: A Case Study in Downtown Lima*, International Finance Corporation, Washington D.C.: World Bank.

Bernal, R., M. Eslava and M. Meléndez (2015), *Taxing Where You Should: Formal Employment and Corporate Income vs Payroll Taxes in the Colombian 2012 Tax Reform*, Preliminary.

Bruhn, M. (2011), *License to Sell: The Effect of Business Registration Reform on Entrepreneurial Activity in Mexico*, *The Review of Economics and Statistics*, February 2011, 93, 382-386.

Bruhn, M. and D. McKenzie (2014), *Entry Regulation and the Formalization of Microenterprises in Developing Countries*, *The World Bank Research Observer* 29: 186-201.

Bruhn, M. and J. Loeprick (2016), *Small Business Tax policy and Informality: Evidence from Georgia*, *International Tax and Public Finance* 23, 834-853.

Card, D., J. Kluge and A. Weber (2017), *What works? A meta analysis of recent active labor market program evaluations*, *Journal of the European Economic Association*, forthcoming.

De Giorgi, G. and A. Rahman (2013), *SME Registration Evidence from a Randomized Controlled Trial in Bangladesh*, *Impact Evaluation Series* 86, Washington D.C.: World Bank.

De Giorgi, G., M. Ploenzke and A. Rahman (2017), *Small Firms' Formalisation: The Stick Treatment*, *The Journal of Development Studies* 2017.

de Mel, S., D. McKenzie and C. Woodruff (2013), *The Demand for, and Consequence of, Formalization among Informal Firms in Sri Lanka*, *American Economic Journal: Applied Economics* 5, 122-150.

Fajnzylber, P., W. F. Maloney and G. V. Montes-Rojas (2011) *Does Formality Improve Micro-firm Performance? Evidence from the Brazilian SIMPLES Program*, *Journal of Development Economics* 94, 262-276.

Maurizio, R. and G. Vázquez (2017), *Formal employment generation and transition to formality in developing countries*, mimeo, ILO: Geneva.

Monteiro, J. C. M. and J. J. Assunção, Outgoing the shadows: estimating the Impact of Bureaucracy Simplification and Tax Cut on Formality and Investment, Working Paper, DAI Brasil.

Pignatti, C. (2017), Enforcement and Compliance with Labour Legislation: The Effect of the Colombian “Action Plan”, International Labour Organization, mimeo, ILO: Geneva.

Rocha, R., G. Ulyssea and L. Rachter (2016), Do Lower Taxes Reduce Informality? Evidence from Brazil, mimeo.

Ronconi, L. and J. Colina (2011), Simplification of Labor Registration in Argentina: Achievements and Pending Issues, IDB Working paper Series No. IDB-WP-277.

### **Studies included in the database**

Alcázar, L. and M. Jaramillo (2016), *The Impact of Formality on Microenterprise Performance: A Case Study in Downtown Lima*, International Finance Corporation, Washington D.C.: World Bank.

Almeida, R. and P. Carneiro (2009), *Enforcement of Labor Regulation and Firm Size*, *Journal of Comparative Economics* 37, 28-46.

Almeida, R. and P. Carneiro (2012), *Enforcement of Labor Regulation and Informality*, *American Economic Journal: Applied Economics* 4, 64-89.

Benhassine, N., D. McKenzie, V. Pouliquen and M. Santini (2017), *Policy Research Working Paper 7900*, Washington D.C.: World Bank.

Bernal, R., M. Eslava and M. Meléndez (2015), *Taxing Where You Should: Formal Employment and Corporate Income vs Payroll Taxes in the Colombian 2012 Tax Reform*, Preliminary.

Betcherman, G., N. Meltem Daysal and C. Pagés (2010), *Do Employment Subsidies Work? Evidence from Regionally Targeted Subsidies in Turkey*, *Labour Economics* 17, 710-722.

Bosch, M., D. Fernandes and J. M. Villa (2015) *Nudging the Self-employed into Contributing to Social Security: Evidence from a Nationwide Quasi Experiment in Brazil*. IDB Working Paper Series, WP 633, Washington D.C.: Inter-American Development Bank.

Bruhn, M. (2011), *License to Sell: The Effect of Business Registration Reform on Entrepreneurial Activity in Mexico*, *The Review of Economics and Statistics*, February 2011, 93, 382-386.

Bruhn, M. (2013), *A Tale of Two Species: Revisiting the Effect of Registration Reform on Informal Business Owners in Mexico*, *Journal of Development Economics* 103, 275-283.

Bruhn, M. and D. McKenzie (2013), *Using Administrative Data to Evaluate Municipal reforms: An Evaluation of the impact of Minas Fácil Expresso*, Impact Evaluation Series No. 85, Washington, D.C.: World Bank.

Bruhn, M. and J. Loeprick (2016), *Small Business Tax policy and Informality: Evidence from Georgia*, *International Tax and Public Finance* 23, 834-853.

Campos, F., M. Goldstein and D. McKenzie (2015), Short-Term Impacts of Formalization Assistance and a Bank Information Session on Business registration and Access to Finance in Malawi, Policy Research Working Paper 7183, Washington D.C.: World Bank.

de Andrade, G. H., M. Bruhn and D. McKenzie (2014), A Helping Hand or the Long Arm of the Law? Experimental Evidence on What Governments Can Do to Formalize Firms, *The World Bank Economic Review* 30, 24-54.

De Giorgi, G. and A. Rahman (2013), SME Registration Evidence from a Randomized Controlled Trial in Bangladesh, *Impact Evaluation Series* 86, Washington D.C.: World Bank.

De Giorgi, G., M. Ploenzke and A. Rahman (2017), Small Firms' Formalisation: The Stick Treatment, *The Journal of Development Studies* 2017.

de Mel, S., D. McKenzie and C. Woodruff (2013), The Demand for, and Consequence of, Formalization among Informal Firms in Sri Lanka, *American Economic Journal: Applied Economics* 5, 122-150.

Fajnzylber, P., W. F. Maloney and G. V. Montes-Rojas (2011) Does Formality Improve Micro-firm Performance? Evidence from the Brazilian SIMPLES Program, *Journal of Development Economics* 94, 262-276.

Fernández, C. and L. Villar (2016), The Impact of Lowering the Payroll tax on Informality in Colombia, *Fedesarrollo Working Paper* No.72.

Kaplan, D. S., E. Piedra and E. Seira (2011), Entry Regulation and Business Start-ups: Evidence from Mexico, *Journal of Public Economics* 95, 1501-1515.

Kugler, A., M. Kugler and L. O. Herrera Prada (2017), Do Payroll Tax Breaks Stimulate Formality? Evidence from Colombia's Reform, *NBER Working Paper Series*, WP23308.

Madalozzo, R. and A. Bruscato Bortoluzzo (2011), The Impact of Tax Exemptions on Labor Registration: The Case of Brazilian Domestic Workers, *Inspere Working Paper* 232.

Monteiro, J. C. M. and J. J. Assunção, Outgoing the shadows: estimating the Impact of Bureaucracy Simplification and Tax Cut on Formality and Investment, *Working Paper*, DAI Brasil.

Morales, L. F. and C. Medina (2016), *Assessing the Effect of Payroll Taxes on Formal Employment: The Case of the 2012 Tax Reform in Colombia*, Borradores de Economía Núm. 971, Banco de la Republica Colombia.

Mullainathan, S. and P. Schnabl (2010), *Does Less Market Entry Regulation Generate More Entrepreneurs? Evidence from a Regulatory Reform in Peru*, *International Differences in Entrepreneurship*, 159-177, NBER, University of Chicago Press.

Pignatti, C. (2017), *Enforcement and Compliance with Labour Legislation: The Effect of the Colombian "Action Plan"*, International Labour Organization, mimeo, ILO: Geneva.

Rocha, R., G. Ulyssea and L. Rachter (2016), *Do Lower Taxes Reduce Informality? Evidence from Brazil*, mimeo.

Ronconi, L. and J. Colina (2011), *Simplification of Labor Registration in Argentina: Achievements and Pending Issues*, IDB Working paper Series No. IDB-WP-277.

Slonimczyk, F. (2012), *The Effect of taxation on Informal Employment: Evidence from the Russian Flat Tax Reform*, *Informal Employment in Emerging and Transition Economies*, Chapter 2, 55-99.

## Appendix A. Search methods for identification of studies

The sampling process of identifying the relevant impact evaluation or quantitative assessment studies for our quantitative review is based on a web search.

### A.1 Search terms

The search strings used in searching the relevant databases (see below) are listed subsequently. These strings are used in a "title" search for relevant publications, to the extent that the advanced search of the respective database allows for such an option. In addition, the terms indicated with an asterisk \* were used in an "abstract" search, too.

- \*Formalize
- \*Formalization
- Market AND entry AND regulation
- Business AND registration
- \*Formality
- Formal AND employment
- Labor AND registration
- Worker AND registration
- Firm AND registration
- Business AND registration
- Bureaucracy AND simplification
- Registration AND simplification
- Labor AND inspection

### A.2 Websites and databases

The following websites, repositories and resources were used to conduct the search:

- SSRN Social Science Research Network (<https://www.ssrn.com/en/>)
- IDEAS (<https://ideas.repec.org/>)
- IZA – Institute of the Study of Labor ([www.iza.org](http://www.iza.org))

- CEPR – Centre for Economic Policy Research ([www.cepr.org](http://www.cepr.org))
- NBER – National Bureau of Economic Research ([www.nber.org](http://www.nber.org))
- 3ie Repository of Published Impact Evaluation Studies  
(<http://www.3ieimpact.org/en/evidence/impact-evaluations/impact-evaluation-repository/>)
- World Bank Open Knowledge Repository (<https://openknowledge.worldbank.org/>)
- Google Scholar (<https://scholar.google.com/>)

### A.3 Inclusion criteria

Key inclusion criteria are the following:

- Study available in English.
- Empirical studies with a quantitative assessment of the effect or impact of a formalization program or policy using some version of a selection correction (counterfactual impact assessment, i.e. estimation of a causal treatment effect). In general, this can include studies based on experimental designs (Randomized Controlled Trials), quasi-experimental or non-experimental methods.
  - Distinguishable estimate of the effect or impact of the formalization program or policy, with an indication of the statistical significance of the estimate.
  - Distinguishable formalization program or policy that can be categorized into one of the four intervention types specified in the coding sheet (see appendix B).
  - Studies that assess the impact on one of the five outcome variables specified in the coding sheet (appendix B).
  - In line with the objectives of the review (see above), and because in general symmetry of effects cannot be assumed, only studies with a "switch-on" type of intervention that target improved formalization outcomes are included. That is, for instance, a study that looks at how tax increases may lead to a reduction in formal employment would not be in-scope.
  - Search hits of studies focusing on the "hidden economy" or "shadow economy" are not in-scope.

## Appendix B. Data extraction

### B.1 Coding

The studies identified for inclusion in the review according to the procedure delineated in appendix A were assessed in detail in order to extract quantitative data for a meta-analytical approach. This information was coded into an excel sheet first, and then in a final version transferred to STATA for the statistical analysis. The coding sheet covers the following variables in the following dimensions:

#### Study characteristics:

- Country
- Authors
- Title
- Publication status (year; journal, if applicable)

#### Intervention characteristics:

- Type of intervention distinguishing four categories: (i) Information interventions, (ii) Simplification / registration interventions, (iii) Financial incentive interventions, such as tax cuts, versions of cost reductions, e.g. social security contributions, etc., (iv) labor inspection.
- Target of the formalization intervention: firms, workers, or both.
- Scope of the intervention: program or policy.
- Name of the intervention
- Outcome(s) assessed in the study: (i) number of registered firms, or firm registration probability, (ii) number of formal jobs, formal employment, or worker registration probability, (iii) wages, (iv) firm profitability, (v) tax revenue.
- If the outcome is (i) or (ii), then extract whether the formalization targeted is (a) fully formal, (b) mixed, (c) something else.
- Year of the policy change or implementation of intervention (if applicable).

#### Empirical analysis:

- Time horizon of the study: start and end
- Unit of observation: (i) firm, (ii) worker, (iii) linked, (iv) other
- Size of the estimation sample (or, if not available: raw data set)
- Data source: (i) administrative record, (ii) survey, (iii) both
- Gender, if the analysis has some specific focus/ results
- Age, if the analysis has some specific focus/ results
- Sectors, if the analysis has some specific focus/ results
- Time horizon of the outcome measurement (in months since reform date / start of the intervention)
- Identification strategy: (i) Randomized Controlled Trial, (ii) Quasi-experimental design, (iii) Non-experimental design
- Empirical method: Difference-in-differences, Regression Discontinuity Design, Propensity Score Matching, etc.
- Sign and statistical significance (convention: 5% level) of the estimated intervention effect or impact: "-1" = negative and statistically significant, "0" = not statistically different from zero, "+1" = positive and statistically significant
- Coefficient of the estimated effect or impact (if available)
- Mean of the outcome in the control group (if available)
- Percent impact of the intervention (if available; naturally this is also coded if the estimated percentage is not statistically different from zero)

#### Background characteristics:

This information typically cannot be extracted from the primary studies, but was extracted from consolidated data bases providing this information (World Bank statistics) and then connected with the individual studies. In general, values will be coded as the respective averages over the study observation period as coded above.

- Annual unemployment rate
- Annual GDP growth

— Formality share

In the coding process, we extracted more than one data row per paper if possible. Typically, this is the case when a paper reports effects for several types of intervention, and/or for several outcomes. Also different estimates for time periods occurred.