Firm Subsidies and Resource Misallocation

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Abstract

Governments in developing and advanced economies subsidize firms in a discretionary fashion. Do such policies mitigate or exacerbate the misallocation of resources across firms? I analyze a typical EU policy using novel data on applicants and recipients of capital subsidies in Greek manufacturing. In my framework, firms face existing distortions that subsidies can correct or exacerbate. The actual policy exacerbates misallocation, decreasing aggregate total factor productivity (TFP) by 0.15%. The policy's potential effects are large as reallocating subsidies among firms can increase TFP by 2% or decrease it by 3%. The actual policy's effect is small because firms facing high distortions are as likely to receive a subsidy as those facing low distortions.

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I Introduction

Governments provide aid to firms to promote agglomeration of industries, direct resources to specific locations,[1] and attenuate the effects of financial or other crises such as the

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[1] The Structural Funds Programme in the EU (Becker et al., 2010) and policies like the Opportunity Zones instituted by The 2017 Tax Cuts and Jobs Act (see Busso et al., 2013; and Kline and Moretti, 2014).

COVID-19 pandemic. Such aid is mostly discretionary—it ends up favoring some firms over others either by design or de facto. Even tariffs that are supposed to apply uniformly and indiscriminately are often not levied equally on all importers of the same good.[2] Discretion at the firm level makes policies powerful enough to correct a variety of distortions. But it can also lead to the misallocation of resources across firms by generating unintended firm-specific distortions or exacerbating existing ones. Recent literature in macroeconomics (Hsieh and Klenow, 2009) shows that firm-specific distortions explain half of the cross-country differences in the aggregate total factor productivity (TFP). Since discretionary aid is widespread among economies[3] and employs substantial resources,[4] several questions arise. Do these policies explain the observed misallocation? How can we implement them to improve allocative efficiency? And to what extent can different implementations of the same government programs increase or decrease aggregate TFP?

This paper makes use of a unique panel dataset of manufacturing firms to analyze a discretionary capital subsidy policy in Greece between 2006 and 2010. The dataset contains information on which firms applied for a subsidy, which received one, and the exact amount of the subsidy transfer. One-third of firms in the dataset applied for a subsidy, and one-fourth received one. The policy establishes an investment subsidy rate, and firms apply for a grant that specifies the amount of investment they would carry out were they to participate in the program. The median participant received a cash transfer equivalent to 10% of its capital stock. In total, the policy allocated transfers equal to 2.8% of the aggregate capital stock, which, in terms of yearly flows, translates to 0.98% of aggregate output. The subsidy data, combined with information on firms' capital stock, wage bill, and value-added production, provide a complete view of firm production decisions and policy implementation.

I study the allocative implications of the subsidy policy using the Hsieh and Klenow (2009) model that features firm heterogeneity in productivity (TFPQ), and firm-specific distortions that drive wedges between the marginal revenue products of capital MRPK and labor MRPK across firms. These wedges lead to resource misallocation reflected in

[2] For instance, in the US, importers can request an exemption from the US Commerce Department, and many receive one (Tankersley, 2018b; Krugman, 2018; Tankersley, 2018a)

[3] Under names like industrial policy or state aid. The OECD defines state aid as follows: "if it involves a certain degree of selectivity, i.e. if it is directed to a specific sector or a specific enterprise, and thus susceptible of significantly distorting competition." See OECD (2010).

[4] The EU transferred 97 billion euros to private enterprises in 2016 representing 0.7 % of its GDP (see the online appendix). Aghion et al. (2015) document that in 2004, 15.1% of all Chinese manufacturing firms received government subsidies. Bartik (2019) estimates that US state and local governments provided $46.3 billion in 2015 in business incentives in the form of tax breaks or cash.

low aggregate TFP and the across-firm dispersion of MRPK and MRPL. Marginal product dispersion maps to two types of distortions: an output distortion and a capital distortion, which are equivalent to firm-specific output and capital taxes. A capital subsidy in this model is an additional capital distortion or a firm-specific negative tax—the subsidy distortion. In an economy with various sources of capital misallocation, the capital distortion consists of a subsidy distortion and a residual one that encompasses all additional sources of distortions.

Data on production help recover the output distortion from the ratio of labor expenditure to nominal output, the capital distortion from the labor-capital expenditure ratio, and the firm-specific productivity (TFPQ) as a residual in the production function. The data on subsidies allows for separately identifying the firm-specific subsidy distortion and the residual capital distortion, facilitating the decomposition of the dispersion of MRPK into a subsidy component and a residual one. Subsidies explain 5.38% of the variance of log MRPK, which is substantial considering that adjustment costs, a well-studied source of MRPK dispersion, explain 1.3% and 11% of the variance among Chinese manufacturers and US publicly listed firms, respectively (David and Venkateswaran, 2019). I calculate the allocative impact of the policy by comparing the TFP of the actual allocation to the one in which the subsidy distortion is zero for all firms. I find that subsidies decreased TFP by 0.15% and explain 0.61% of the observed misallocation measured as TFP loss. Why do subsidies explain only 0.61% of misallocation while explaining more than 5% of the log MRPK variance? The reason is that, in the Hsieh and Klenow (2009) model, the output distortion is responsible for most of the MRPK and MRPK dispersion, but a capital subsidy has no bearing on that distortion.

To explore how the mapping of MRPK in the data to the capital distortions affect the estimated impact of subsidies on TFP, I generate results from an alternative model in which there are only capital distortions but neither labor nor output ones. In this alternative model, like in the static version of David and Venkateswaran (2019), MRPL is equalized across firms, misallocation comes only from the capital distortion, and subsidies explain 5.83% of the variance in log MRPK and 3.28% of the misallocation and decrease TFP by 0.44%. Thus, the two models produce qualitatively similar results: subsidies reduce TFP and explain observed misallocation. Their magnitude, though, depends on the specification of distortions beyond the capital market—in the output and labor markets. This insight suggests that specifying distortions beyond the market directly affected by a policy is crucial for quantifying its allocative implications. This paper uses the methodology of Hsieh and Klenow (2009) as its baseline because such modeling leaves no observed dispersion of MRPK and MRPL unaccounted for in the data.

This quantitative framework allows for calculating best- and worst-case scenarios of the implementation of subsidy policies. The best-case scenario arises by reallocating subsidies to maximize TFP while keeping the policy expenditure equal to the actual one. Analogously, the worst-case scenario results from reallocating the subsidies to minimize TFP. In the best-case scenario, TFP increases by 2.22%, while in the worst-case scenario, it decreases by 3.55%. Such figures serve as an ex-ante policy evaluation tool as they can provide bounds on the potential allocative impact of the policy given the structure of existing distortions and the size of the policy's budget. These bounds also serve as an ex-post policy evaluation tool by providing benchmarks with which to compare the actual policy. For example, the actual policy leads to a 0.15% drop in TFP, which is small compared to the lower bound that is twenty times as large. On the other hand, the actual policy is a missed opportunity as it could have boosted TFP, and hence aggregate output, by more than 2%. An output gain of this magnitude is substantial, even taking into account the cost of public funds for such policy, which is estimated to be roughly 0.27% of total output. But how can such sizeable potential TFP gains be realized?

To answer this question, I examine the characteristics of the firms subsidized under the TFP-maximizing policy. I find that the most constrained firms in the dataset—those with large MRPK and MRPL—should be subsidized. These firms also tend to have high firm-specific productivity (TFPQ), which is driven by the positive empirical relationship between distortions and productivity TFPQ in this dataset, like in many other datasets studied in the literature. Other observable firm characteristics such as size or age bear no weight in the probability of being subsidized under the TFP-maximizing counterfactual, suggesting that selecting firms into the policy based on those characteristics is unlikely to improve TFP. In contrast to the TFP-maximizing counterfactual, the actual policy subsidizes constrained firms and unconstrained ones with equal odds, which explains why the overall effect on TFP is small. Also, the TFP-maximizing policy reallocates subsidies among all firms in the dataset, which may be desirable but not implementable given the constraints policymakers may face.

To address this concern, I exploit data on firms who applied for a subsidy and reallocate subsidies only among them. A counterfactual reallocation of this kind is arguably easier to implement and increases TFP by 1.02% that is still higher than the estimated cost of public funds. That TFP gain, however, is half of the one resulting from optimally reallocating subsidies among all firms, which suggests that eligibility criteria or firm self-selection can be crucial for the successful design of policies. The data from the actual policy reveal that, in terms of distortions, the set of applicants is nearly a random draw from the firm population, and the set of participants is nearly a random draw from the applicant pool. This fact may indicate that improving allocative efficiency was not the intended purpose of the policy.

This model implies that two firms that face different distortions but are otherwise identical respond differently to the same subsidy—essentially, the treatment effects are heterogeneous—consistently with empirical studies finding substantial heterogeneity in the responses of firms to policy (Zwick and Mahon, 2017; Chen et al., 2016). In this model, when capital becomes cheaper (is subsidized), a firm facing lower distortions expands its capital more than a firm facing higher ones. For instance, if distortions reflect bureaucratic red tape, a firm that finds it difficult to acquire a license for building a brand new factory may forgo investing despite it becoming cheaper through subsidies. Alternatively, it may be hard for a firm facing financial constraints to fully capitalize on cheaper capital because it still needs to finance investment. This latter mechanism is at the center of the model by Gopinath et al. (2017), who show that as interest rates drop, making the flow cost of capital cheaper, financially constrained firms grow less than financially unconstrained ones. As a result, misallocation increases. A similar mechanism is at play in this paper as well. A uniform subsidy to all firms increases misallocation because firms facing lower distortions acquire more resources than those facing higher ones, leading to lower TFP. Indeed, my results show that reallocating the policy resources by making capital uniformly cheaper across all firms decreases TFP by 0.7%—a worse outcome than the actual policy. Such a mechanism is relevant for industrial policies whose textbook case prescribes sector-specific subsidies (see, for instance, Bartelme et al., 2019).

Contribution. This paper contributes to the literature on misallocation that was pioneered by Restuccia and Rogerson (2008), and Hsieh and Klenow (2009). It does so by exploring the quantitative importance of discretionary subsidy policies as a potential cause of misallocation. Restuccia and Rogerson (2017) divide the potential causes of misallocation into three categories: market imperfections, statutory provisions, and discretionary provisions made by governments, or other entities (such as banks), that favor or penalize specific firms. This paper investigates the role of the last and least-explored category: discretionary provisions. Despite being prevalent, discretionary policies are not well-studied from a misallocation viewpoint because of the lack of data. Data on firm-specific subsidies in the EU are have become more widely available since 2016 when the European Commission made the disclosure of information on state aid recipients mandatory. The novel data used in this paper has a panel structure that allows for identifying distortions from persistent differences in factor shares across firms, thus mitigating recent concerns about possible measurement error in results from cross-sectional studies. Bils et al. (2020) raise that issue and highlight that the panel structure of datasets can purge some of the measurement error from the calculation of distortions. As in this paper, a number of recent studies, such as Adamopoulos et al. (2017) and Boehm and Oberfield (2018), use the panel structure of the data to purge the calculation of distortions from some measurement error.

Even though the policy studied in the paper explains only 0.61–3.28% of the TFP loss, such discretionary policies potentially have a larger impact. That is because they have the power to change the ranking of firms in the size distribution, which Hopenhayn (2014) shows is necessary to achieve large TFP effects. That paper shows that policies that preserve the rank of firms in the firm size distribution, such as size-dependent policies, are unlikely to have significant effects on the aggregate TFP. A discretionary subsidy policy that spends 1% of the capital stock in subsidies (approximately 1/3% of aggregate output, which is a lower bound on the actual government aid) can, however, change TFP between -8% and +2% in an economy calibrated to US manufacturing. Given that David et al. (2019) find that in 11 developed and developing countries more than 50% of the dispersion in MRPK is unexplained by either technology, dynamics, or markups, discretionary policies are worth exploring.

This paper takes a different methodological approach than the two prevailing ones in misallocation literature—the direct and the indirect—according to Restuccia and Rogerson (2013, 2017). The direct approach quantifies the effect of a specific mechanism on misallocation, marginal product dispersion, and TFP. Examples of such mechanisms are information frictions, as in David et al. (2016); a technology featuring dynamics, as in Asker et al. (2014) or David and Venkateswaran (2019); a land-allocation policy, as in Adamopoulos et al. (2017); distorted endogenous firm entry, as in Bento and Restuccia (2017); or financial frictions, as in Midrigan and Xu (2014) or Gopinath et al. (2017). The indirect approach, on the other hand, quantifies the overall TFP losses from misallocation in different environments by measuring wedges in the firms' optimality conditions, as in Hsieh and Klenow (2009), Bartelsman et al. (2013), and Oberfield (2013). This paper uses a combination of the two approaches as it quantifies the effect of a particular mechanism, capital subsidies, on TFP, and simultaneously quantifies the overall extent of misallocation within the same framework using the same dataset. Such a hybrid approach admits a decomposition of the observed misallocation into subsidies and other factors, which is not possible using any of the two conventional approaches alone. This decomposition allows for evaluating the importance of a specific distortion relative to other distortions. I call this approach hybrid following Asker et al. (2019), who also use the hybrid approach to study the impact of curtailing oil extraction by OPEC countries on the dynamic efficiency of global oil extraction.

Another feature of this paper setting it apart from the rest of the literature is that the mechanism it studies can either increase or decrease misallocation and TFP. This feature is useful when studying policy interventions as it does not constrain policies to be necessarily TFP reducing. Since most policies are well-intended and aimed at improving market outcomes, using a framework flexible enough to allow for the possibility to increase TFP seems particularly appropriate.

By allowing subsidies to be TFP-improving, this model provides a framework for studying optimal policy in the presence of distortions. Recently, there has been renewed interest in the study of optimal industrial policy. Itskhoki and Moll (2019) study optimal taxation in developing countries using a dynamic environment with financial frictions, where credit subsidies are welfare-improving. Bartelme et al. (2019) and Lashkaripour and Lugovskyy (2019) study optimal tariffs and optimal value-added taxes in an international trade context with distortions at the sectoral level. In all those papers, the optimal policy addresses well-specified market failures: financial frictions, scale or agglomeration economies, or market power. In this paper, in contrast, the source of distortions is unspecified (a black box). A disadvantage of models focusing on a particular market failure is that they ignore other frictions that generate variation in the data—such models are not saturated. A shortcoming of unsaturated models is that policy recommendations may have unintended consequences. My framework, in contrast, is saturated. It takes a holistic view of market failures in the capital, labor, and output markets—albeit in a black-box fashion—and is, therefore, comprehensive as it provides an assessment of potential unintended consequences of focused policy interventions by taking into account the universe of distortions.

This paper examines a type of policy that has been the focus of recent studies: government aid to firms. Kalouptsidi (2018) and Barwick et al. (2019) analyze the effect of subsidies to the Chinese shipbuilding industry on the entry and growth of firms, industry revenue, and producer surplus, with a focus on evaluating the effects of different policy instruments (entry subsidies, production subsidies, or investment subsidies). Criscuolo et al. (2019) study a capital subsidy policy in the UK, similar to the policy analyzed in this paper, with a focus on the policy's impact on employment. Slattery and Zidar (2020) examine the policy of local business incentives in the USA and discuss the tradeoff between discretion and transparency in the allocation of resources. Slattery (2020) studies how local governments compete for firms by offering them incentives to locate within their borders. Aghion et al. (2015) study how industrial subsidies in China affect firm-specific productivity growth. This paper studies a similar policy from a misallocation point of view to evaluate its impact on aggregate TFP. Since TFP explains the majority of the sizeable differences in output per worker across countries (Jones, 2016), and misallocation is responsible for half of manufacturing TFP differences across some countries (Hsieh and Klenow, 2009), studying the allocative implications of the widespread government aid to firms seems natural and very relevant.

The remainder of the paper is organized as follows. Section II describes the empirical setting, and Section III develops the model and characterizes the policy bounds. Section IV describes the dataset and presents misallocation facts. Section V presents the quantitative analysis, and Section VI concludes. The online appendix includes formula derivations, details about the data, and additional results.

II Institutional setting: The discretionary subsidy policy

The Greek government has been aiding firms at least since the 1970s.[5] A central instrument through which the state aids firms is investment grants, which are rewards in the form of either tax credits or cash transfers. Such state aid is regulated by congress through legislation that is referred to as *the development law*. Each significant modification of the *the development law* constitutes a different subsidy program. Aid to firms by member states of the EU is regulated by EU law; therefore, these Greek subsidy programs abide by EU regulation. The main restriction that the EU imposes on these programs is geographical. Essentially, states face constraints when subsidizing firms in geographical areas that are not designated 'disadvantaged.' This is because the EU allows state aid only for the purpose of lowering the disparities in economic conditions among regions, and, therefore, all state aid in the EU is under the umbrella of *regional policy*. These *development laws*

[5]For an historical perspective on state aid to firms in Greece, see Papaioannou (2010).

have been modified either because of changes in the Greek government leadership or because new EU legislation rendered current programs illegal. This paper focuses on three such programs spanning the years 1998–2013. The first program (code named 2601) started in 1998 and approved 684 million euro of transfers to approximately 1,600 firms; the second program (code named 3299-A) started in 2004 and approved 1.4 billion euro of transfers to approximately 2,100 firms; and the third program (code named 3299-B)[6] started in 2006 and approved 2.9 billion euro of transfers to approximately 4,200 firms. These programs provide aid to many sectors of economic activity, but this paper focuses on the manufacturing sector.

The predominant policy instrument is a cash subsidy on fixed capital investment expenditure with other policy instruments being subsidies on interest payments, subsidies on the lease of equipment (if they are leased instead of purchased) or tax credits. In particular, 80% of the grants in the first program and 97% of the grants in the two subsequent programs are in the form of cash subsidies on investment expenditure. Since investment subsidies are the dominant policy instrument, this paper focuses on these and disregards the other instruments. Each program specifies a set of subsidy rates that depends mainly on the geographic location in which the investment takes place. All three subsidy programs are implemented through a granting process: firms submit an application for inclusion in the program and the institutions administering the program accept or reject applications on a case-by-case basis. The three programs received a total of approximately 11,000 grant applications, and a just under 8,000 grants were allocated, indicating that for every five grant applications there are approximately four acceptances. Rejecting or accepting the application is at the government's discretion. If an application is accepted, the firm is included in the program and the government contributes the percentage of the capital expenditure according to the location-specific subsidy rate, which varies between 25% and 60%. This granting process of the subsidy policy implies that the program is not a textbook version of a subsidy policy, in the sense that subsidized firms can spend any amount they like on capital investment. Any investment the firm incurs beyond the amount specified in the grant is not subsidized. Therefore, the outcome of this policy is that firms participating in the program have paid for only a fraction of their productive capital, while the government has paid for the remaining fraction.

The stated goals of these policies are very broad. The Greek government's stated goal is

[6] The *development law* of 2004 needed to change in 2006 because the map of 'disadvantaged' areas was redrawn by the EU in 2006. Therefore, the *development law* of 2006 is the second version of the 2004 *development law*—hence the code names 3299-A and 3299-B.

the assistance of disadvantaged regions and the modernization of the economy. The EU's stated goal of such policies is regional convergence, EU cohesion, and growth. This paper does not evaluate these programs in terms of their efficacy in achieving their stated goals but, rather, evaluates the allocative implications of such programs through their impact on the aggregate TFP. Such discretionary policies are common across EU states, and the EU administration recognizes the potentially distortionary role of discretionary subsidies. In fact, one of the five functions of the Directorate-General for Competition of the European Commission, whose main objective is tackling market distortions, is the enforcement of state aid control. A 2016 competition policy brief by the Directorate discusses "...public interventions that might have potentially distortive effects on competition and on intra-EU trade, i.e. government aid that confers selective advantages to companies." To avoid the distortionary role of state aid, the State Aid Modernisation Programme of 2014 required that state aid to firms needs to be public at the grant level starting in 2016. This Greek government program has potentially distortionary effects that matter for the aggregate economy. This is because of the intensity of the policy reflected in the 25–60% subsidy rate on investment and the size of the three programs that spent approximately five billion euros. To put this number into perspective, it represents 20% of the non-residential investment[7] in the Greek economy in 2005.

III A Model of aggregate TFP and firm-specific distortions

This section presents a model of monopolistic competition featuring heterogeneous firms to measure the effect of capital subsidies on resource misallocation. In addition to firm heterogeneity due to efficiency, output, or capital distortions (as in Hsieh and Klenow, 2009), there is a policy intervention in the capital market generating an additional firm-specific capital distortion. The policy may alleviate or exacerbate existing *structural* distortions. Within this framework, we can also characterize a TFP-maximizing set of capital subsidies under a variety of constraints. The online appendix contains derivations of formulas and model simulations.

[7] Non-residential investment is calculated by subtracting the investment in dwellings from the total fixed investment in current prices for all NACE activities. The data come from Eurostat's `nama_10_nfa_fl` dataset.

III.1 Production technology, firm choice, and the aggregate TFP

Consider an economy or an industry populated by a fixed number of firms N, each choosing capital and labor inputs to produce an intermediate differentiated product using a Cobb-Douglas production technology. The production function of the differentiated product of a firm i combines firm productivity A (TFPQ), capital K, and labor L to produce output $Y_i = A_i K_i^{\alpha} L_i^{1-\alpha}$.

These intermediate differentiated products Y_i are bundled together by a competitive firm using a CES technology to generate a final good that represents aggregate output $\mathbf{Y} = \left[\sum_{i=1}^{N} Y_i^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$. Cost minimization by the competitive firm implies that the demand function for an intermediate good i with price p_i is $Y_i = \left(\frac{p_i}{\mathbf{P}}\right)^{\eta} \mathbf{Y}$. The price $\mathbf{P}$ of the final good, which takes the form of $\left[\sum p_i^{1-\eta}\right]^{\frac{1}{1-\eta}}$, is set to unity because the final good is considered the numeraire; hence, the inverse demand function for the output of firm i is $p_i = Y_i^{-\frac{1}{\eta}} \mathbf{Y}^{\frac{1}{\eta}}$.

The problem of the firms. The N firms each producing one of the N differentiated intermediate goods are monopolistic competitors. Each firm i chooses an amount of capital K_i and labor L_i to maximize profits given market-wide factor prices and firm-specific distortions. In particular, the profits of firm i are given by $\pi_i = (1 - \tau_{Yi}) p_i Y_i - wL_i - (1 + \tau_{Ki}) RK_i$.

This profit function includes an output distortion τ_Y that drives a firm-specific gap between market revenues and revenues captured by the firm, and a firm-specific capital distortion τ_K that generates a firm-specific price of capital. These two distortions affect the firms' choice of inputs and generate differences in marginal products of capital and labor across firms.

The aggregate TFP. The aggregate TFP or aggregate productivity is defined as the scalar wedge between aggregate output $\mathbf{Y}$ and a Cobb-Douglas transformation of the aggregate capital and labor $\mathbf{TFP} \equiv \frac{\mathbf{Y}}{\mathbf{K}^{\alpha}\mathbf{L}^{1-\alpha}}$, where the aggregate capital and labor are the sum of the two factors across all firms $\mathbf{K} \equiv \sum_{i=1}^{N} K_i$, $\mathbf{L} \equiv \sum_{i=1}^{N} L_i$. Given an amount of aggregate inputs of capital $\mathbf{K}$ and labor $\mathbf{L}$, higher TFP reflects higher aggregate output. Allocative efficiency implies that the allocation of resources across firms depends only on the efficiency levels A_i (TFPQ) and that the aggregate TFP depends solely on efficiency levels, as well. Indeed, in this model, the efficient aggregate TFP is $\text{TFP}_{\text{efficient}} = \left[\sum_{i=1}^{N} A_i^{\eta-1}\right]^{\frac{1}{\eta-1}}$. If the allocation in the economy depends not only on firm efficiency but also on firm-specific output and capital distortions, the TFP depends also on firm-specific distortions and is equal to

$$\text{(1)} \qquad \mathbf{TFP}\left(\{A_i, \tau_{Yi}, \tau_{Ki}\}_i\right) = \frac{\left(\sum \frac{[(1-\tau_{Yi})A_i]^{\eta-1}}{(1+\tau_{Ki})^{\alpha(\eta-1)}}\right)^{\frac{\eta}{\eta-1}}}{\left(\sum \frac{(1-\tau_{Yi})^{\eta} A_i^{\eta-1}}{(1+\tau_{Ki})^{1+\alpha(\eta-1)}}\right)^{\alpha} \left(\sum \frac{(1-\tau_{Yi})^{\eta} A_i^{\eta-1}}{(1+\tau_{Ki})^{\alpha(\eta-1)}}\right)^{(1-\alpha)}} .$$

The TFP formula in equation (1) shows that for allocative-efficiency, what matters is the dispersion in the output and capital wedges $1-\tau_Y,\ 1+\tau_K$ but not their levels. In fact, multiplying all wedges by a positive scalar cy, ck—i.e., $1+\tau_{Kit} \mapsto (1+\tau_{Kit})ck$, $1-\tau_{Yit} \mapsto (1-\tau_{Yi})cy$, leaves the TFP unchanged.

Misallocation measurement. The extent of misallocation in the economy can be quantified in terms of the TFP loss because of distortions and, in particular, as the relative difference between the *structural* TFP and the efficient TFP: $\mathbf{TFP}_{\text{loss}} = 1 - \mathbf{TFP}/\mathbf{TFP}_{\text{efficient}}$. The TFP loss formula shows that the degree of misallocation depends on the dispersion in firm-specific productivity A but not on its level. In fact, multiplying firm productivities by a positive scalar c ($A_{it} \mapsto A_{it}c$) leaves the TFP loss unchanged.

The effect of policies on the dispersion of firm-specific distortions is the focus of this paper since its goal is to analyze the allocative implications of policies. Equation (1), which maps distortions to the allocative efficiency index **TFP**, is the central analytical tool in this paper and the following section develops a framework for distinguishing the role of a policy from other residual factors in a prevailing 'observed' allocation that is reflected in the prevailing 'observed' distortions $\{\tau_{Yi}, \tau_{Ki}\}_i$.

III.2 Policy distortions and *residual* or *structural* or *policy-invariant* distortions

This section of the paper defines the policy and the *residual* (or *structural*) components of the capital distortion and further clarifies the meaning of *structural*. A subsidy on capital drives a wedge between the actual cost of capital that a firm faces and the cost of capital that a firm would face in the absence of the policy. Without the policy, firms would nonetheless face different costs of capital for reasons unrelated to the policy itself.

These definitions provide the basis of an accounting and policy-analysis framework: an accounting framework in the sense that it decomposes any observed wedges to a policy component and a *residual* component; and a policy analysis framework in the sense that, by assuming that the *residual* component is *policy invariant* or *structural*, it measures how the policy affects the resource allocation in the economy.

The prevailing 'observed' distortion, the policy distortion, and the residual distortion. Consider a firm whose behavior is consistent with facing a capital distortion of τ_K. Such a prevailing distortion is equivalent to a tax: instead of paying the market price R for capital, the firm actually pays price $(1+\tau_K)R$. If the distortion τ_K is negative, it is practically a subsidy. A tax or subsidy policy generates a distortion τ_p between the market price R and the policy-adjusted price $(1+\tau_p)R$. The policy distortion τ_p together with the distortion due to unrelated (residual) factors $\hat{\tau}_K$ make up the composite prevailing distortion τ_K that rationalizes the firm's behavior. Therefore, we may say that the residual distortion is the difference between the composite prevailing distortion and the policy distortion.

Definition 1. *The residual capital distortion $\hat{\tau}_{Ki}$ is the prevailing capital distortion τ_{Ki} net of the policy distortion τ_{pi}.*

$$\hat{\tau}_{Ki} \equiv \tau_{Ki} - \tau_{pi} \Leftrightarrow \tau_{Ki} \equiv \tau_{pi} + \hat{\tau}_{Ki}.$$

The focus of this paper is a subsidy policy, and, hence, the policy distortion is either zero or negative for all firms. Firms that are not subsidized through the policy have a policy distortion of zero and in the accounting framework of equation (1), their composite prevailing distortion is equal to their residual distortion. Subsidized firms have a negative policy distortion. For instance, suppose that a firm's behavior is rationalized by a 30% distortion such that this firm appears as if it pays $(1+0.3)R$ for capital instead of the market price R. The wedge of 0.3 is the composite distortion τ_K in equation (1). Also, suppose that this firm already receives a 10% capital subsidy from the government–that is, the firm would pay 10 percent more for capital in the absence of the policy. Thus, without the subsidy, the firm would pay 30 plus 10, or 40% above the market price. In the accounting framework of equation (1), the policy distortion τ_p is -0.1 because a subsidy is a negative tax, and the residual distortion $\hat{\tau}_K$ is $0.4 = 0.3 - (-0.1)$. In essence, in the absence of the policy, firms would pay more for capital. Strictly speaking, without the policy, firms would pay at least as much for capital since an unsubsidized firm would pay the same price for capital either with or without the policy.

***Policy-invariant* (*structural*) distortion.** This paper considers *residual* distortions to be *policy-invariant* or *structural*. The capital distortion net of the policy distortion—i.e., the residual distortion—is the component unexplained by the policy, perhaps because it emanates from distortions unrelated to the policy under study or from market imperfections. Such residual distortions are considered structural in the sense that they are invariant to the policy under study: they are present regardless of the policy's budget or its allocation. This paper, which aims to analyze a specific capital subsidy policy, considers the residual capital distortions and output distortions to be *policy-invariant*—that is to say *structural*, as stated in the following assumption.

Assumption 1. *The residual capital distortion $\hat{\tau}_{Ki}$ is policy-invariant (structural). The output distortion τ_{Yi} and the firm-specific productivity A_i are also policy-invariant.*

This assumption implies that if the subsidy policy is removed, the remaining capital and output distortions are unchanged and so are the firm-specific productivities. This assumption is the basis of a policy evaluation framework, as it implies that we can remove the subsidy policy by setting the policy distortions to zero ($\tau_{pi} = 0$) and calculate the aggregate TFP emerging solely from the structural capital and output distortions $\hat{\tau}_{Ki}, \tau_{Yi}$. This paper takes the structural approach to evaluating the economic impact of policy. According to the structural approach, which was established by Marschak (1953), a set of policies is described and a theoretical framework specifies which model components do not vary with the policy; the policy-invariant components have traditionally been referred to as structural. In this study, the firm-specific productivity, the output distortion, and the residual capital distortion—the capital distortion that is not explained by the observed subsidy policy—are considered structural. Consequently, the model permits me to perform counterfactual experiments in which the subsidy policy is perturbed, keeping the joint distribution of A and the structural distortions constant. As Hurwicz (1966) clarified, structural does not mean invariant to any policy but, rather, invariant to the specified perturbations of the particular policy of interest.[8] In accordance with this idea, the structural distortions in this paper do not imply that these distortions are assumed to be inherent to the Greek manufacturing sector. Instead, the implication is that they remain constant relative to changes in the implementation of the capital subsidy policy which is a

[8]For an exposition of the structural approach to policy evaluation with examples from recent applications, see Heckman (2000), Heckman and Vytlacil (2007) and the references therein.

much weaker assumption than invariance to any intervention. Recent papers using the structural approach to study the effects of policies on misallocation include Garicano et al. (2016) who study the allocative implications of size-dependent policies in France. In brief, my paper studies an industrial subsidy policy by comparing the actual policy outcome with alternative allocations by explicitly stating these counterfactual allocations, a feature that, according to Rodrik (2008, p. 9), most studies of industrial policies lack.

The invariance assumption, however, imposes no restrictions on the joint distribution of distortions and policy. In particular, the model allows for a very flexible data generating process $\left(A_i, \tau_{Yi}, \hat{\tau}_K, \tau_p\right)$ when one takes the model to the data and does not assume that the policy is statistically orthogonal to the distortions.

III.2.1 Counterfactual allocations

***Structural* allocation, misallocation, TFP.** The degree of misallocation emerging solely from the *structural* distortions in the economy is henceforth referred to as *structural* misallocation. The *structural* allocation of resources across firms in an economy with technology parameters η, α is characterized by the set of *structural* firm-specific efficiency and distortions $\{A_i, \tau_{Yi}, \hat{\tau}_{Ki}\}_i$. A measure of the allocative efficiency of the *structural* allocation is the *structural* TFP given by $\widehat{\mathbf{TFP}}\left(\{A_i, \tau_{Yi}, \hat{\tau}_{Ki}\}_i\right)$. The degree of *structural* misallocation is measured as the relative difference between the *structural* TFP and the efficient TFP—i.e., $\mathbf{TFP}_{\text{loss}} = 1 - \widehat{\mathbf{TFP}}/\mathbf{TFP}_{\text{efficient}}$. Since the policy of interest for this paper is already in effect, the prevailing allocation reflects both *structural* and policy distortions, and therefore, the *structural* allocation is counterfactual. The TFP formula $\widehat{\mathbf{TFP}}\left(\{A_i, \tau_{Yi}, \hat{\tau}_{Ki} + \tau_{pi}\}_i\right)$ is the central structural equation used for counterfactual policy analysis as it depends solely on structural parameters (distortions and A) and policy (τ_p), but not on endogenous quantities such as firm inputs or output.

The policy effect on TFP. Does the policy improve upon this existing *structural* allocation, leave allocative efficiency unchanged, or exacerbate misallocation? The obvious route to answering such a question is to compare the TFP of the prevailing allocation, which is affected by the policy, with the *structural* TFP that is unrelated to the policy. Consequently, the effect of the policy on the aggregate TFP in terms of a percentage increase is defined as $\frac{\mathbf{TFP}}{\widehat{\mathbf{TFP}}} - 1$.

The assumption of the *policy-invariance* of the output distortion and the residual capital distortion implies that the structural distortions are constant throughout the counterfactual analysis presented in Section V. Therefore, all the results in this paper are conditional on the existing *structural* distortions in the economy.

Comparing the TFP of the economy with and without the policy quantifies the allocative implications of the policy relative to the existing *structural* allocation, but it would be useful to also know how different implementations of the same policy instrument would have affected allocative efficiency. An important difference of this paper's setting from the literature—and a novelty of this paper—is that the subsidy policy can mitigate existing misallocation improving allocative efficiency. Therefore, the next section studies optimal policy design of capital subsidies by characterizing the reallocation of the policy's resources that maximizes TFP.

III.3 Model implications

This model has two general qualitative implications, one about firm behavior, and one aggregate. First, firms respond differently to the same subsidy, which is to say that treatment effects are heterogeneous. Second, a non-discretionary—uniform—subsidy may decrease aggregate TFP. Both results stem from firms facing different structural distortions. Model simulations and general analytical arguments can be found in the online appendix.

III.3.1 Implication I: Treatment effects are heterogeneous

In this model a firm with low structural capital distortion $\hat{\tau}_{Ki}$ expands its capital input more than a firm with a high structural capital distortion $\hat{\tau}_{Ki}$ even if they receive the same subsidy τ_{si}. Suppose that firm 1 faces a zero structural distortion $\hat{\tau}_{K1} = 0$ and firm 2 faces a structural distortion of 1, and both firms receive a 50% subsidy $\tau_s = 0.5$. For firm 1, the cost of capital drops from 1 to 0.5, a 50% drop, but for firm 2, the cost of capital drops from 2 to 1.5, a 25% drop. Therefore, firm 1 expands its capital more than firm 2 even if they receive the same subsidy.

This implication is consistent with an environment in which implicit structural wedges represent distortions in the market for capital that are not necessarily reflected in the acquisition price of machinery and equipment. Such distortions may arise from size-dependent borrowing constraints, as in Gopinath et al. (2017). In their dynamic model, firms with high net worth have higher borrowing capacity than firms with low net worth. In their model, a decrease in the real interest rate results in a much larger expansion of capital by high-net-worth firms relative to low-net-worth firms because the former can take advantage of this lower cost of capital because, unlike the latter, they have the ability to borrow. Therefore, a drop in interest rates generates higher dispersion in MRPK and reduces aggregate TFP. A similar mechanism is at play in this paper. A uniform subsidy decreases the component of the cost of capital that is common among firms, but firms respond differently to this decrease in the cost of capital because they face different *structural* capital distortions. In addition, the capital and output distortions represent a variety of market imperfections and policy distortions that are unlikely to be directly reduced by a subsidy on an input to production (See Restuccia and Rogerson (2017) for a taxonomy of the causes of such distortions). It is more plausible that a subsidy reduces the overall acquisition cost of an input by directly affecting only the cost component that is common among all firms.

Consider a model economy defined by $\{A_i, \tau_{Yi}, \hat{\tau}_{Ki}, \tilde{\tau}_{si}\}_{i=1}^{N}$. The equilibrium capital for a firm i is given by equation (2), where $\mathbf{K}$ is the aggregate capital in the economy

$$K_i(A_i, \tau_{Yi}, \hat{\tau}_{Ki}) = \frac{\frac{(1-\tau_{Yi})^{\eta} A_i^{\eta-1}}{(1+\hat{\tau}_{Ki})^{1+\alpha(\eta-1)}}}{\sum \frac{(1-\tau_{Yi})^{\eta} A_i^{\eta-1}}{(1+\hat{\tau}_{Ki})^{1+\alpha(\eta-1)}}} \mathbf{K}. \tag{2}$$

Suppose that firm 1 faces a *structural* capital wedge equal to 1, while firm 2 faces a *structural* capital wedge equal to $1 + \hat{\tau}_{K2},\ \hat{\tau}_{K2} > 0$. The two firms are otherwise identical. Now, suppose that both firms receive a subsidy τ_s. What happens to the capital stock of the two firms? What happens to the dispersion between their marginal products of capital?

The ratio of the capital stock between these two firms is $K_1/K_2 = (1+\hat{\tau}_{K2})^{1+\alpha(\eta-1)} > 1$. Since the aggregate capital stock remains constant, the ratio of the capital stock between these two firms becomes $K_1(\tau_s)/K_2(\tau_s) = \frac{(1-\tau_s+\hat{\tau}_{K2})^{1+\alpha(\eta-1)}}{(1-\tau_s)^{1+\alpha(\eta-1)}}$. The capital of firm 1 increases proportionately more than the capital of firm 2. To see this, note that $K_1(\tau_s)/K_2(\tau_s) = \left[\frac{1-\tau_s+\hat{\tau}_{K2}}{1-\tau_s}\right]^{1+\alpha(\eta-1)}$. And $K_1(\tau_s)/K_2(\tau_s) > K_1/K_2$ because $\frac{1-\tau_s+\hat{\tau}_{K2}}{1-\tau_s} > 1+\hat{\tau}_{K2}$.[9] That relationship implies that with the same subsidy, the firm with the smaller structural distortion expands its capital more than the firm with the larger structural distortion since $K_1(\tau_s)/K_1 > K_2(\tau_s)/K_2$.

Alternatively, to explore response heterogeneity, consider a subsidy to a single firm i. Since the effect of a single subsidy barely changes the denominator of the capital demand equation (2) let's focus only on the numerator (a partial equilibrium approximation).

[9]To see why the inequality is true, notice the following chain of equivalences: $(1-\tau_s) < 1 \Leftrightarrow \hat{\tau}_{K2}(1-\tau_s) < \hat{\tau}_{K2} \Leftrightarrow \hat{\tau}_{K2}(1-\tau_s) + 1 - \tau_s < \hat{\tau}_{K2} + 1 - \tau_s \Leftrightarrow (1+\hat{\tau}_{K2})(1-\tau_s) < 1 + \hat{\tau}_{K2} - \tau_s \Leftrightarrow 1 + \hat{\tau}_{K2} < \frac{1+\hat{\tau}_{K2}-\tau_s}{1-\tau_s}$.

The effect of a subsidy on capital demand $K(1-\tau_s+\hat{\tau}_{Ki})/K(1+\hat{\tau}_{Ki})$ is approximately $\approx \left[\frac{1+\hat{\tau}_{Ki}}{1-\tau_s+\hat{\tau}_{Ki}}\right]^{1+\alpha(\eta-1)}$. Notice that for large enough distortions ($\hat{\tau}_{Ki} \to \infty$) that ratio is unity implying that a subsidy has no effect on capital demand at all. After taking logs, that ratio equals to $[1+\alpha(\eta-1)][\log(1+\hat{\tau}_{Ki})-\log(1-\tau_s+\hat{\tau}_{Ki})]$. To see how this response is affected by the size of the distortion take the derivative with respect to $\hat{\tau}_{Ki}$, which equals to $[1+\alpha(\eta-1)][\frac{1}{1+\hat{\tau}_{Ki}}-\frac{1}{1-\tau_s+\hat{\tau}_{Ki}}] < 0$ which negative. That means that the larger the distortion, the smaller the response of capital demand to a subsidy.

This model feature of heterogeneous firm responses to government aid is consistent with empirical studies finding heterogeneous treatment effects (elasticities). For instance, Zwick and Mahon (2017) study the effect of the tax incentive of bonus depreciation on firm investment, and one of their central results is that the investment response to the policy is heterogeneous and that such heterogeneity points towards models with financial frictions or adjustment costs, or a mix of these factors. In this model, such factors are reflected in the capital or output distortions.[10]

III.3.2 Implication II: A uniform subsidy may decrease TFP

The uniform subsidy increases the dispersion of MRPK between the two firms above. Since the two firms have identical output distortions, the ratio of their marginal products of capital is $MRPK_2/MRPK_1 = 1+\tau_{K2} > 1$. With the subsidy, the ratio of the two marginal products of capital becomes $MRPK_2/MRPK_1 = \frac{1+\tau_{K2}-\tau_s}{1-\tau_s}$. The dispersion of MRPK increases because $\frac{1+\tau_{K2}-\tau_s}{1-\tau_s} > 1+\tau_{K2}$.[11] This inequality is equivalent to $\frac{1+\tau_{K2}-\tau_s}{1+\tau_{K2}} > 1-\tau_s$ which is equivalent to $1-\frac{1+\tau_{K2}-\tau_s}{1+\tau_{K2}} < 1-(1-\tau_s) = \tau_s$. This says that the percentage decrease in the cost of capital because of the subsidy is larger for the firm facing the lowest structural distortion. A more general argument about the relationship between a uniform subsidy and its effect on allocative efficiency is developed in the online appendix.

Simulations on a model economy calibrated to match the misallocation facts for the US manufacturing that a uniform capital subsidy of 1% reduces TFP by 0.5% by increasing the misallocation in the model economy (see the online appendix for details). This is an interesting result because it implies that the simplest policy, from an implementation point of view, can be damaging in terms of allocative efficiency and not misallocation-neutral. The textbook case for industrial policy suggests that sectors subject to external economies of scale should be subsidized through a sector-specific subsidy (see, for instance,

[10] Chen et al. (2016) also find that firms respond differently to tax incentives for R&D investment.
[11] As shown in the paragraph above discussing the firm-level implications of the model.

Bartelme et al., 2019). In the presence of firm-specific distortions, however, such a sector-specific uniform subsidy may have the unintended consequence of lowering sectoral TFP. Interestingly, Rodrik (2008) argues that uniform or 'horizontal' policies usually have asymmetric effects that may be distortionary. Therefore, a uniform subsidy is not a good benchmark with which to compare the success of the policies.

A uniform subsidy in a model with only capital distortions. In a model with distortions only in the capital market, a small uniform subsidy is always TFP decreasing, which is consistent with the model by Gopinath et al. (2017), which features only capital distortions (see the online appendix).

III.4 Policy bounds

What is the upper bound of the impact of capital subsidies on TFP given a set of constraints? And how should they be allocated to achieve it? What is the lower bound of their impact on TFP, on the other hand? That is, what is the worst-case scenario of the policy instrument of capital subsidies? This section extends the model for characterizing policy bounds by solving TFP-maximization and TFP-minimization subsidy-allocation problems.

III.4.1 The upper bound: TFP-maximizing subsidies

The purpose of policy interventions in input and output markets is to correct market failures that, in my framework, are quantified by the *structural* capital and output distortions. This section defines and characterizes capital subsidy policies that maximize aggregate TFP subject to various constraints. Under these constraints, the optimal policy will not, in general, achieve the undistorted (i.e., misallocation-free) allocation, and, therefore, they are *second-best* policies. Put differently, this section characterizes how we would allocate subsidies, were we to take the implications of the framework of Hsieh and Klenow (2009) and Restuccia and Rogerson (2008) seriously. Seriously, in the sense that policy strives to eliminate the *structural* distortions $\hat{\tau}_{Ki}$ and τ_{Yi}. Such exercise is subject to all the caveats discussed in the literature.[12]

[12] Undeniably, such distortions may not be entirely distortionary because the model might be misspecified. Nevertheless, this misallocation framework provides a powerful conceptual apparatus to think about the evaluation of policies in terms of their impact on allocative efficiency and aggregate TFP.

Definition of the optimal-policy problem The optimal policy is a set of firm-specific subsidies $\{\tilde{\tau}_{si}\}_i$ that maximizes the aggregate TFP subject to a budget constraint and a non-negativity constraint of the subsidies that prohibits the policy maker from taxing firms. The non-negativity constraint is set so that the optimal policy is as close as possible to the constraints of the subsidy policy analyzed in this paper. While subsidies are often discretionary at the firm level, there are either institutional constraints that prevent taxes from being discretionary at the firm level or the policy maker administering the subsidy program makes decisions independently from corporate tax policy. The budget constraint of the policy is expressed in terms of the real capital $\mathbf{K}_s$. A subsidy $\tilde{\tau}_{si}$ to firm i implies that the firm will maximize its profit at a capital stock equal to $K_i(A_i, \tau_{Yi}, \hat{\tau}_{Ki}, \tilde{\tau}_{si})$, and the transfer to the firm by the policy maker will equal to $\tilde{\tau}_{si} K_i(A_i, \tau_{Yi}, \hat{\tau}_{Ki}, \tilde{\tau}_{si})$. The policy's budget constraint implies that the total transfers by the policy maker should be $\mathbf{K}_s$. A subsidy $\tilde{\tau}_{si}$ to firm i brings its capital distortion to $\hat{\tau}_{Ki} - \tilde{\tau}_{si}$.

$$
\begin{aligned}
&\max_{\{\tilde{\tau}_{si}\}_{i=1}^N} \mathbf{TFP}(\{A_i, \tau_{Yi}, \hat{\tau}_{Ki}, \tilde{\tau}_{si}\}_{i=1}^N) \\
&\text{s.t.} \sum_{i=1}^N \tilde{\tau}_{si} K_i(A_i, \tau_{Yi}, \hat{\tau}_{Ki}, \tilde{\tau}_{si}) = \mathbf{K}_s, \quad 0 \leq \tilde{\tau}_{si}.
\end{aligned}
\tag{3}
$$

Since the focus of the policy analysis is on allocative efficiency, the aggregate capital $\mathbf{K}$ and labor $\mathbf{L}$ are kept constant throughout the analysis. The policy affects only the allocation of capital and labor but not their aggregate quantities. In this setting, maximizing **TFP** is equivalent to maximizing aggregate output keeping aggregate capital and labor fixed. By substituting the formulas for TFP and firm-level, profit-maximizing capital $K_i(A_i, \tau_{Yi}, \hat{\tau}_{Ki}, \tilde{\tau}_{si})$ the optimal policy problem can be written as

$$
\begin{aligned}
&\max_{\{\tilde{\tau}_{si}\}_{i=1}^N} \frac{\left(\sum \frac{[(1-\tau_{Yi})A_i]^{\eta-1}}{(1+\hat{\tau}_{Ki}-\tilde{\tau}_{si})^{\alpha(\eta-1)}}\right)^{\frac{\eta}{\eta-1}}}{\left(\sum \frac{(1-\tau_{Yi})^{\eta} A_i^{\eta-1}}{(1+\hat{\tau}_{Ki}-\tilde{\tau}_{si})^{1+\alpha(\eta-1)}}\right)^{\alpha} \left(\sum \frac{(1-\tau_{Yi})^{\eta} A_i^{\eta-1}}{(1+\hat{\tau}_{Ki}-\tilde{\tau}_{si})^{\alpha(\eta-1)}}\right)^{(1-\alpha)}} \\
&\text{s.t.} \sum_{i=1}^N \tilde{\tau}_{si} \frac{\frac{(1-\tau_{Yi})^{\eta} A_i^{\eta-1}}{(1+\hat{\tau}_{Ki}-\tilde{\tau}_{si})^{1+\alpha(\eta-1)}}}{\sum \frac{(1-\tau_{Yi})^{\eta} A_i^{\eta-1}}{(1+\hat{\tau}_{Ki}-\tilde{\tau}_{si})^{1+\alpha(\eta-1)}}} = \frac{\mathbf{K}_s}{\mathbf{K}}, \quad 0 \leq \tilde{\tau}_{si}.
\end{aligned}
\tag{4}
$$

In this formulation of the problem, the budget constraint is cast in relative terms: the share capital in the economy allocated through the policy $\frac{\mathbf{K}_s}{\mathbf{K}}$. The left-hand side of the budget constraint is in terms of the share capital of subsidized firms in the economy: $\sum_{i=1}^{N} \tilde{\tau}_{si} \frac{K_i}{\mathbf{K}}$.

Properties of the optimal policy. The problem of finding the optimal policy in equation (4) is a non-linear optimization problem with N unknowns that does not have a closed-form solution. Nonetheless, algebraic manipulations of the problem's first-order conditions[13] show that the optimal subsidy of subsidized firms has the following parametric form:

$$\tilde{\tau}_{si} = \frac{C_0 + C_k \frac{1+\hat{\tau}_{Ki}}{1-\tau_{Yi}} + C_{yk}(1+\hat{\tau}_{Ki})}{1 - C_y \frac{1}{1-\tau_{Yi}}}. \tag{5}$$

Even though the coefficients C_0, C_K, C_Y, C_{KY} have no closed form, the functional form of the solution is helpful for two reasons. First, it is a guide to which variables are relevant if we want to approximate the solution, and second, it reduces the computational complexity of the optimal policy problem if we know the set of subsidized firms. If we know the set of subsidized firms, then we need only solve for four unknowns, C_0, C_K, C_Y, C_{KY}, reducing the number of unknowns from N to four. This means that the computational complexity of the problem can be substantially reduced if we can accurately predict the set of subsidized firms. We can approximate the set of subsidized firms by solving the full non-linear optimization problem on a small representative sample of firms and then estimating a selection model that we can then use to select the set of subsidized firms on the full sample. For a demonstration of how the functional form simplifies the numerical solution of the problem, see the online appendix. The optimal policy is a function of a firm's output wedge $\frac{1}{1-\tau_{Yi}}$, which is proportional to the firm's *structural* marginal product of labor $\widehat{MRPL}_i$; a function of $\frac{1+\hat{\tau}_{Ki}}{1-\tau_{Yi}}$, which is proportional to the firm's *structural* marginal product of capital $\widehat{MRPK}_i$; and a function of the firm's capital wedge $1+\hat{\tau}_{Ki}$, which is proportional to the the ratio of the firm's structural marginal products of capital and labor $\frac{\widehat{MRPK}_i}{\widehat{MRPL}_i}$. Since there is no closed-form solution for the function of the optimal subsidy, this paper explores the quantitative properties of the function by simulation.

[13]See the online appendix for the derivation of the formula.

III.4.2 The lower bound: TFP-minimizing subsidies

The lower bound of a subsidy policy given a budget constraint is the solution of the optimization problem in (4) , but with a min operator instead of a max operator. The functional form of the optimal subsidy to subsidized firms is the same as in equation (5), even though the set of subsidized firms and the undetermined coefficients will be different than the ones for the TFP-max policy.

III.5 Discussion of a model with only capital distortions

The decomposition of the capital distortion into a structural one and a policy one would have different allocative implications were we to assume that there are distortions only in the capital market but none in the output or labor markets as in David and Venkateswaran (2019). In that model, there is no dispersion in the MRPL, and the MRPK equals $1 + \check{\tau}_K$—i.e., the capital distortion explains all the variation in the MRPK. The equations characterizing the TFP loss from misallocation in that model are simpler because they do not depend on the joint distribution of capital and output distortions. As a result, in that model, it is analytically shown that a small uniform subsidy is always TFP decreasing. A capital subsidy changes the MRPK to $1 + \check{\tau}_K - \tau_s$. In contrast, in the Hsieh Klenow model, which this paper follows, a subsidy changes the MRPK form $(1 + \tau_K)/(1 - \tau_{Yi})$ to $(1 + \tau_K - \tau_s)/(1 - \tau_{Yi})$. For an exploration of the single-distortion model, see the online appendix.

III.6 Implications from a model calibrated to US manufacturing

Discretionary subsidies can have a large impact on TFP. To gain a sense of the quantitative implications of the theoretical framework, I perform policy counterfactuals on a model economy calibrated to the misallocation facts of US manufacturing. A policymaker allocates capital subsidies to firms constrained by a budget equal to 1% of the aggregate capital stock. Assuming that the share of the aggregate capital expenditure RK is one-third of output, the budget is equivalent to a third of a percent of aggregate output. That figure is reasonably close to the 0.28% the US federal government spends as a share of GDP for capital transfers to firms and much lower than the 1.25% that the EU spends (see the online appendix for these figures). I find that TFP-maximizing subsidies increase TFP by up to 2%; a uniform subsidy decreases TFP by 0.5–1%; and, in the worst-case scenario, subsidies decrease TFP by 3.4–8% (see the online appendix for details). These figures suggest that subsidies can have a substantial impact on TFP—either positive or negative.

IV Data and empirical approach

This section presents the data sources and describes the mapping of the data to the model.

IV.1 Datasets for production and subsidies

The data on production are drawn from Greece's Annual Survey of Manufactures (EBE) conducted by the Greek government's official statistical organization ELSTAT which is a member of the European Statistical System and provides most statistics on Greece to Eurostat including the data on the construction of the national accounts. The EBE is a census of all registered manufacturing firms in Greece with at least ten employees. The survey provides information on firm characteristics at a yearly frequency, and the dataset has a panel structure as each observation contains a firm identifier. The variables in the EBE that I use are the firm's employment, gross purchases of capital goods, labor and material expenditure, and sales. Even though subsequent revisions to the Greek government debt and deficit have cast doubt on the credibility of the Greek fiscal statistics, the quality of the primary sources of production data like the ones used in this study was never in question (see the online appendix for additional information).

Balance sheet data for firms spanning 1999–2010 come from ICAP, the company supplying the data for Greece to the ORBIS global database of firms (see Kalemli-Ozcan et al., 2015). The variables in the balance sheet dataset I use are the book value of capital stock, the depreciated book value of capital stock, and the firm's year of establishment, which I use to construct the firm's age.

Data for subsidies come from Greece's Ministry of Development, an administrative division of the Treasury department of the Greek government, responsible for the general oversight of programs providing state aid to firms. The administrative data on subsidies provide information on grant applicants and program participants during the years 1998–2010. The unit of observation in the subsidy dataset is an application by a firm for a grant, which includes the application year, the proposed capital expenditure, and the size of the grant. An implicit investment subsidy rate can be calculated by dividing the grant size by the proposed capital expenditure. For the applicants that received grants to participate in the program, there is also information on the year in which the grant was authorized.

The three firm-level datasets above are merged to create the sample used in the analysis. After data cleaning, there are approximately 2,000 firms in the sample and 1,200 firm observations per year, with the median firm employing 36 employees and being 18 years in operation. That sample covers 1/4 of manufacturing employment and 36% of the labor expenditure (see the online appendix for additional information). Given the incomplete sectoral coverage, the results of this paper regarding the aggregate TFP do not directly map to the productivity series in the national accounts but, still, they are insightful about the allocative implications of subsidies. Approximately one fourth of the firms in the sample applied for a grant, and a fifth of all firms participated in one of the three programs. One tenth of the firms in the sample received two subsidy grants during the years 1998–2013, but the median participant firm received a single grant. For every five grant applications by the manufacturing firms in the sample, four applications were successful. The maximum investment subsidy rate was 60%, and 95% of the program participants received a subsidy between 20% and 55%, with the median investment subsidy rate at 35%.

IV.2 Empirical methodology

Parameterization. I begin by assigning values to the two parameters of the model: the elasticity of output with respect to capital α and the elasticity of substitution between firm output η. I set $\alpha = 0.35$ as in Gopinath et al. (2017), which corresponds to the average capital share in a relatively less distorted economy such as the US. I set $\eta = 3$, as is standard in the literature (Gopinath et al., 2017; Hsieh and Klenow, 2009).

Measurement of production flows. As is customary in the literature, I measure the expenditure on a firm's output $p_{it}Y_{it}$ by the firm's value added, which is calculated by subtracting the materials expenditure from sales in current prices, where the subscript t denotes time in units of years. A firm's labor expenditure wL_{it} is measured by the total labor expenditure in current prices. Capital is measured by the net book value of fixed assets by subtracting the accumulated depreciation of fixed assets from the gross book value of fixed capital. I set the rental price of capital $R = 0.1$, as in Hsieh and Klenow (2009).

Measuring the prevailing distortions and TFPQ$_{it}$. The first step of the analysis to recover the prevailing distortions and firm-level productivity $\{1 - \tau_{Yit}, 1 + \tau_{Kit}, A_{it}\}_{it}$, which rationalize the prevailing allocation for every year in the dataset. The mapping of the data to the output and capital wedges is derived from the first-order conditions of the firm's optimization problem, which are derived in the online appendix. I follow Hsieh and Klenow (2009) in recovering the output wedge as the ratio of the nominal value added to the wage bill, the capital wedge as the ratio of the wage bill to the cost of capital RK_{it}, and the TFPQ$_{it}$ as the ratio of real output Y_{it} to $K_{it}^{\alpha}L_{it}^{1-\alpha}$, after converting the nominal output to real using the formula $Y_{it} = (p_{it}Y_{it})^{\eta/(\eta-1)}$. I then proceed by trimming and rescaling the data. The online appendix describes the process in detail.

IV.2.1 Comparing the dataset to the literature

To put this novel dataset in perspective, I compare the extent of misallocation in manufacturing in Greece to the on in the US, China, and Indian as calculated by HK. To do so, I calculate the yearly TFP loss for misallocation (TFP loss) and average it across all the available years. The TFP loss for Greece is 30%, for the USA 27%, China 50%, and India 52%. These figures suggest that the misallocation in Greek manufacturing is more severe than in the USA but less so than in China or India. That is consistent with the ranking of these four countries in terms of TFP as, according to the Feenstra et al. (2015), the economy-wide TFP in Greece, China, and India is lower by 29%, 63%, and 71%, respectively, relative to the USA.[14] These differences in the extent of misallocation across the four countries are consistent with the patterns of dispersion in the TFPR and MRPK. The degree of firm heterogeneity in firm productivity in this dataset is similar to the datasets from the USA, China, or India. The dispersion in TFPQ$_i$ (the standard deviation of $\log A$) is 0.95 compared to 0.83, 1.0, and 1.19 in the USA, China, and India. Even though the dispersion in firm-specific productivity has no bearing on misallocation, the purpose of this comparison is to show that this dataset is not fundamentally different from datasets used in other studies in terms of firm heterogeneity. The online appendix contains a detailed exposition of the misallocation facts along with cross-country comparisons of data patterns.

IV.2.2 Mapping the subsidy data to the model

The combined dataset on firm characteristics and subsidies is a panel of firms with information at a yearly frequency. If firm i's grant application is accepted in year t, the dataset provides information on the size of the investment project and the cash transfer from the government. The investment subsidy rate is the share of the government's contribution to the investment project and is calculated by dividing the the cash transfer by the investment project. The main decision a firm makes regarding the policy is the grant application,

[14]Still, a country's rank in terms of TFP does not necessarily correspond to its rank in terms of misallocation. Nonetheless, since according to HK, misallocation explains half of manufacturing TPF differences, it is reasonable to expect that TFP differences reflect differences in misallocation.

which specifies how much it is willing to invest, given the subsidy rate. If the grant is approved, the firm carries out the investment. Thus, any existing distortions affecting the responsiveness of the firm to the policy matter at the application stage and are reflected in the realized capital stock of subsidized firms.

The investment project does not necessarily have to be carried out in the same year the grant application is accepted. If all investment projects were completed in the same year the subsidy is granted, then gross investment that year should be at least as large as the size of the investment project. But in the data, the median subsidy grantee's gross investment (purchase of capital goods) is 40% the size of the investment project. In fact, for three fourths of the grantees, gross investment in the year of the application acceptance is less than the size of the investment project specified in the grant.[15] There are many potential explanations for why firms do not carry out the whole investment project within the year in which the government grants the subsidy: for example, the acceptance date is close to the end of the year, or the investment project involves the construction of a plant that takes more than one year to complete.

Whatever the reason behind the delay in materializing the investment project, it has implications for how the data are mapped to the model. What is the capital policy distortion $\tau_{s_{it}}$? Is it the subsidy rate on investment? How many years past the acceptance of the grant application does the firm stop facing a subsidy distortion? The subsidy rate of the grant does not exactly map on the policy distortion $\tau_{s_{it}}$, as firms cannot purchase any amount of capital at discount because the investment project in the grant application is the maximum amount of investment at the favorable rate. Therefore, the investment subsidy rate promised to a given program participant is an upper bound on the policy distortion $\tau_{s_{it}}$.

This paper aims to quantify the contribution of discretionary policies in the measured misallocation in the manufacturing sector. Therefore, when mapping the subsidy data to the model, the objective is to quantify whether the fact that some firms have or had access to cheaper capital than other firms can explain the observed allocation. In this paper, I map the subsidy data to τ_s by calculating the percent of capital stock a firm acquired for free through the subsidy policy. Essentially, I recover τ_s by calculating the average discount on the price of capital a firm faces due to the policy. To do so, for each subsidized firm, I calculate a series for the capital stock that a firm got for free K_{it}^{free}. The subsidy

[15]For these calculations, I use the variable from the EBE survey that reports the purchases of capital goods for each firm rather than the net investment.

policy distortion is then calculated as the ratio between the actual capital stock and the free capital stock $\tau_{s_{it}} = K_{it}^{free}/K_{it}$.[16] This way of calculating the policy distortion is a lower bound on the policy distortion, leading to conservative estimates of the effect of the policy on allocative efficiency. An advantage of this approach of calculating the policy distortion is that such discretionary policies are allowed to generate long-term distortionary effects. Such long-term effects are likely for several reasons. First, policy rules prohibit firms from reselling the subsidized capital within the first five years of the grant. Therefore, firms cannot buy the capital cheaply in the year in which they received the subsidy and resell it imediately at market price, pocketing the profit. This constraint implies that if subsidies are directed to firms with already low distortions, the subsidized capital remains with the firm long after the year of the subsidy, even though they would have rather sold part of their capital. Second, investment in some capital goods exhibits partial irreversibility; that is, once acquired, the capital goods either cannot be resold or can be sold at a large discount.[17] For these two reasons, subsidy policies are likely to have implications in the long run that are captured using the average subsidy approach ($\tau_{s_{it}} = K_{it}^{free}/K_{it}$) for calculating the subsidy policy distortion. Besides, this paper aims to quantify the effect of discretionary policies on allocative efficiency and their potential role in the observed misallocation in the economy, not to measure the short-run responses of firms to such policies.

Table 1 shows the recovered capital policy distortion τ_s in the dataset. The median $\tau_{s_{it}}$ among subsidized firms is 0.1, which implies that 10% of the capital stock is paid by the government. The median subsidy among subsidized firms is very stable across years, but the number of subsidized firms increases with time. This is because the majority of the grants in the dataset were given from 2006 to 2010, with one third of the grants given in 2006 alone. An additional reason that the share of firms with a positive capital subsidy distortion increases is that if a firm has been subsidized in the past, it will always have a positive distortion, although the distortion will keep getting closer to zero as the free capital stock depreciates. Since the goal of this paper is to investigate the aggregate effects of discretionary policies, from now on I will focus on the years 2006–2010, when the policies had a substantial presence in the economy.

[16] The online appendix contains details about recovering τ_s from the data.

[17] For evidence of capital specificity and the resale discount (investment irreversibility), see Ramey and Shapiro (2001).

Table 1: The recovered capital policy distortion from the longitudinal dataset

Year	'99	'00	'01	'02	'03	'04	'05	' 06	' 07	' 08	'09	'10
% $\tau_{s_{it}} > 0$	0.1	1	1	2	3	3	5	15	16	23	26	27
$\text{Med}(\tau_{s_{it}} \vert \tau_{s_{it}} > 0)$	0.1	0.04	0.1	0.09	0.08	0.09	0.09	0.08	0.09	0.12	0.1	0.1

IV.2.3 Constructing the cross-sectional dataset for the quantitative analysis.

To reduce the importance of outlier observations, I *winsorize* the dataset by setting the value of observations above the 90th percentile equal to the 90th percentile value and setting the value of observations below the 10th percentile equal to the value of the 10th percentile of each marginal distribution of the variables $1 - \tau_Y$, $1 + \tau_K$, and A. The *winsorization* of the three distributions does not discard any observations—unlike trimming—but brings outlier observations closer to the median. Hsieh and Klenow (2009) show that outlier observations may have a substantial impact on the absolute number of the measured TFP losses from misallocation, but even excluding outliers, the TFP losses remain large, which is true in this dataset as well. Keeping the design of a misallocation-reducing policy at the firm level in mind, it is better to avoid outliers, or else the policy might end up focusing on the few firms that appear either extremely productive or extremely constrained. Besides, the *winsorization* of the productivity A distribution preserves the ranking of firms in terms of productivity (TFPQ), and the the *winsorization* the output wedge $1 - \tau_Y$ distribution preserves the ranking of the marginal product of labor $MRPL \propto \frac{1}{1-\tau_Y}$ distribution. Even though the simultaneous trimming of the output and capital wedges does not necessarily preserve the ranking of the MRPK, the Spearman rank correlation of the MRPK before and after *winsorization* is 0.98, suggesting that the ranking of the MRPK observations is nearly unchanged.[18] Therefore, the most (least) constrained or productive firms remain the most (least) constrained or productive after the *winsorization*.

I exploit the panel structure of the data by reducing the firm-year longitudinal dataset of wedges and firm-specific productivity $\{1 - \tau_{Yit}, 1 + \tau_{Kit}, A_{it}, \tau_{s_{it}}\}_{it}$ to a firm cross-sectional dataset $\{1 - \tau_{Yi}, 1 + \tau_{Ki}, A_i, \tau_{s_i}\}_i$ by substituting all observations for each firm by its average—i.e., $1 - \tau_{Yi} = (1/T)\sum_{t=1}^{T} 1 - \tau_{Yit}$, $1 - \tau_{Ki} = (1/T)\sum_{t=1}^{T} 1 - \tau_{Kit}$, $A_i = (1/T)\sum_{t=1}^{T} A_{it}$, and $\tau_{s_i} = (1/T)\sum_{t=1}^{T} \tau_{s_{it}}$ for the policy-intensive years 2006–2010. This panel measure of wedges and firm-specific productivity at the firm level is less subject to transitory variation that may be prone to mismeasurement and may exaggerate the cross-sectional variation in the firm-year data. Adamopoulos et al. (2017) and Bils et al.

[18]The Spearman rank correlation of the TFPR before and after *winsorization* is 0.97.

(2020) exploit the panel structure of datasets to purge the data from potential measurement error. The approach of this paper is closer to that of Adamopoulos et al. (2017), who average resources across years for Chinese farms, but unlike that paper, I first calculate yearly wedges and TFPQ_{it} and then take averages.[19] After the dataset is reduced, the composite capital wedge $1 + \tau_K$, the output wedge $1 - \tau_K$, and the firm-level productivity (TFPQ) A are rescaled by dividing by the sample median.[20] The budget of the policy $\frac{\mathbf{K}_s}{\mathbf{K}}$ is calculated by dividing the capital that the government paid for each firm in the dataset $\sum_i \tau_{s_i} K_i$ by the total capital stock—i.e., $\frac{\mathbf{K}_s}{\mathbf{K}} = \sum_i \tau_{s_i} K_i / \sum_i K_i$. The policy budget represents the fraction of the capital stock in the economy paid by the government and maps directly to the budget of the optimal subsidy policy problem defined and characterized in Section III.

A number of recent quantitative studies (David and Venkateswaran, 2019; Asker et al., 2014) show that some of the observed variation in the marginal revenue product of capital is explained by the dynamic nature of the decision to invest, which static models such as the one in this paper abstract away from. Nonetheless, David and Venkateswaran (2019) show that approximately one half of the MRPK dispersion in their datasets from China and the US is left unexplained, and they attribute this to firm-specific distortions. In addition, the authors find that these firm-specific distortions are permanent rather than transitory—that is, they appear as a firm fixed component.[21] By reducing the firm-year longitudinal dataset to a firm cross-sectional dataset, this paper aims to explore whether subsidies are responsible for these permanent firm-specific distortions that lead to the misallocation of resources in the economy. Do some firms have consistently higher marginal products of capital and labor and, if so, is discretionary policy the reason? This paper attempts to answer this question.

The dataset $\{1 - \tau_{Yi}, 1 + \tau_{Ki}, A_i, \tau_{s_i}\}_i$ used for the quantitative analysis includes 1,413 firms, one fourth of which have a positive capital subsidy distortion; in other words, they are subsidized. Among subsidized firms, the average subsidy τ_{s_i} is 11% and the maximum subsidy is 48%. One third of the firms in the dataset applied for a subsidy

[19]Adamopoulos et al. (2017) mention that if they first calculate farm-year-specific TFP and then average TFP across years instead of averaging resources across years and then calculating farm-specific TFP, their results are nearly identical.

[20]The TFPR and the MRPK are recalculated using the rescaled wedges and productivities by the fomulas $TFPR_i = \frac{\eta}{\eta-1}\left(\frac{1}{\alpha}\right)^{\alpha}\left(\frac{1}{1-\alpha}\right)^{1-\alpha} R^{\alpha}\frac{(1+\tau_{Ki})^{\alpha}}{1-\tau_{Yi}}$ and $MRPK_i = \frac{1+\tau_{Ki}}{1-\tau_{Yi}}$.

[21]Indeed, in the dataset of this paper—for the years between 2006 and 2010, which are used for the quantitative analysis—the share of the standard deviation in $\tau_{Kit}, \tau_{Yit}, \tau_{Ait}$ that is coming from the across-firm dispersion is at least two thirds (0.88, 0.65, and 0.80, respectively).

sometime between 1998 and 2010, but one in every five of these applicants did not receive a subsidy. The budget of the policy $\frac{\mathbf{K_s}}{\mathbf{K}}$ in the dataset is 0.028, implying that 2.8% of the total capital stock in the data is paid by the subsidy program. The dispersion in firm-specific productivity TFPQ and TFPR in the dataset is substantial and similar to the numbers reported by Hsieh and Klenow (2009) for the USA. Specifically, the 75/25 ratio of firm-level TFPQ is 3.1-fold compared to 3.2-fold in the USA, and the 75/25 ratio of firm-level TFPR is 1.64-fold compared to 1.6-fold in the USA. The loss in TFP from the misallocation of resources in this dataset is 20.1%, implying a potential gain from reallocation of 25%. This degree of misallocation is lower than the one reported from the yearly cross-sections in Section IV.2.1 because the averaging of wedges and productivities across years for each firm reduced the variation in the data, and the *winsorization* of the distributions of wedges and productivities diminished the importance of outliers.

IV.2.4 Mapping the data to a model with only capital distortions

Even though the formulas developed in this paper carry over from a model featuring two distortions to one featuring only capital-market distortions $\check{\tau}_{Ki}$, the mapping from the data to the model is different. For results from a single-distortion model, the capital market wedge is $1 + \check{\tau}_{Ki} = (1 + \tau_{Ki})/(1 - \tau_{Yi})$, the output distortion is zero, and the structural capital distortion is $\widehat{\check{\tau}}_{Ki} = \check{\tau}_{Ki} + \tau_{s_i}$ (see the online appendix for details).

V Quantitative analysis

This section presents the results of the quantitative analysis in three steps. First, I calculate the effect of the actual policy on the aggregate TFP and the variance of the MRPK. Second, I compare the TFP arising from the actual policy to the one form several counterfactual policies, including the upper and lower bounds. Third, I analyze the TFP-maximizing policy at the firm level to investigate which type of firm would receive a subsidy if the goal was to reduce misallocation. The aggregate analysis in steps one and two presents results both from the baseline model featuring capital and output distortions and an alternative model featuring only distortions in the capital market. The third step focuses solely on the baseline model.

V.1 The decomposition: the impact of the observed subsidies on TFP

Table 2 compares the prevailing 'observed' allocation in the dataset—which includes the subsidy policy distortion—with two counterfactual allocations. One that arises by removing all subsidies and one by reallocating them in the form of a uniform subsidy to all firms. Essentially, Table 2 transforms the allocation $\{1 - \tau_{Yi}, 1 + \hat{\tau}_{Ki} - \tau_{s_i}, A_i\}_i$ by setting either all subsidy distortions to zero $\tau_{s_i} \mapsto 0$, or the subsidy distortion to every firm to the same uniform subsidy $\tau_{s_i} \mapsto \bar{\tau}_s = 2.8\%$.

Decomposing the dispersion of the MRPK. I start by decomposing the variance of the prevailing 'observed' log MRPK distribution into a component coming from the policy and a residual one coming from other factors, the structural component. Subsidies explain 5.38% of the variance of the log MRPK in the baseline model and 5.83% in the alternative model. This is a substantial effect. To put this number in perspective, consider that, according to David and Venkateswaran (2019), adjustment costs explain 1.3% of the variance among Chinese manufacturers and 11% of the variance among US publicly listed firms. In essence, subsidies explain a similar portion of the variance that a salient source of dynamics explains.

The impact of the actual policy on allocative efficiency (TFP). The finding that emerges from Table 2 is that the subsidy policy decreased aggregate TFP by 0.15%. Therefore, the subsidy policy program exacerbated rather than mitigated the existing structural misallocation in the manufacturing sector. The structural misallocation expressed as the TFP loss relative to the efficient allocation is 20.02% while the prevailing 'observed' misallocation is 20.14%, which implies that the subsidy policy explains 0.61% of the measured misallocation in the dataset. Even though the policy explains more than 5% of the variance of the log MRPK, it explains a mere 0.61% of misallocation. That is because a capital subsidy leaves distortions that only affect the MRPL unchanged. Indeed, the policy explains only 0.51% of the variance in log TFPR, which is the measure that reflects all distortions in the baseline model. Mapping all distortions in MRPK to a single distortion in the capital market, thus assuming that the labor market is undistorted as in David and Venkateswaran (2019), leads to an effect on TFP of -0.44%, which explain 3.28% of the TFP loss (bottom panel in Table 2). For formulas from a model with a single source of distortions, see the online appendix.

Table 2: Main results I: The effect of subsidies and the uniform counterfactual

Statistic	Allocations: Uniform* (Counterf.) $\widetilde{X}$	Observed (Factual) X	*Structural* (Counterf.) $\widehat{X}$	Subsidies explain[§] % $100 \max\{\frac{X-\hat{X}}{X}, 0\}$
	Baseline model with output and capital distortions			
ΔTFP from $\widehat{X}$ %	-0.72	-0.15	0.0	
TFP loss %	20.59	20.14	20.02	0.61
Var log MRPK	0.508	0.508	0.480	5.38
Var log TFPR	0.133	0.131	0.130	0.51
	Alternative model with only capital distortions			
ΔTFP from $\widehat{X}$ %	-0.80	-0.44	0.0	
TFP loss %	12.28	11.96	11.57	3.28
Var log MRPK	0.510	0.508	0.478	5.83

The table compares the observed allocation in the data that is generated from a composite capital distortion $\tau_{Ki} = \hat{\tau}_{Ki} - \tau_{s_i}$, which includes the *structural* distortion $\hat{\tau}_{Ki}$ and the subsidy policy distortion τ_{s_i}, with a counterfactual allocation generated after setting all subsidy policy distortions equal to zero.
*Under the uniform subsidy policy, the subsidy rate is the same among all firms and equal to $\tau_{s_i} = \tau_s = 0.028$, which requires the same budget as the actual policy.
[§]The decomposition makes sense only if X is greater than or equal to $\hat{X}$. The max operator in the formula highlights this point and guarantees that only sensical results are reported.

The counterfactual uniform policy. The potential effect of a uniform policy is informative because it provides a low-bar benchmark against which to compare any policy. Uniform policies are easy to implement by statutorily subsidizing capital for all firms. Since in this model, a uniform subsidy is not TFP-neutral (see section III.3), just because the actual policy decreased TFP does not mean that it performed worst that a hypothetical uniform subsidy. Indeed, Table 3 shows that the actual policy performs better than the uniform, which leads to a TFP decrease of 0.72% (Table 2). The negative effect of the uniform subsidy is an empirical result as the sign of the effect depends on the covariance of the two distortions. In contrast, in the alternative model featuring only distortions in the capital market, a hypothetical uniform subsidy always decreases TFP. In this dataset, it would decrease TFP by 0.80% (bottom panel in Table 2).

V.2 Counterfactual policy bounds

I investigate the potential effect of a capital subsidy policy with the same budget as the actual one (2.8% of the aggregate capital) on TFP by calculating upper and lower bounds given various constraints on the firms who are allowed to receive subsidies, the admissible set $\mathbb{A} \subset \{1, \ldots, N\}$. That set includes actual recipients of a subsidy (participants), or applicants for one, or all firms in the dataset. The counterfactual best- and worst-case scenarios are, fundamentally, reallocations of the subsidy budget, each time among different firms with the objective of either maximizing or minimizing TFP. Expression (6) presents the TFP-maximization problem, and the TFP-minimization problem is analogous with a min operator in place of the max. Table 3 presents the results.

$$\begin{aligned} &\max_{\{\tilde{\tau}_{si}\}_{i=1}^{N}} \mathbf{TFP}(\{\tilde{\tau}_{s_i}, \cdot\}_{i=1}^{N}) \\ &\text{s.t. } \sum_{i=1}^{N} \frac{\tilde{\tau}_{s_i} K_i(\tilde{\tau}_{s_i}, \cdot)}{\mathbf{K}} = 2.8\% \\ &\text{s.t. } 0 \leq \tilde{\tau}_{s_i} \text{ for all } i \text{ and } \tilde{\tau}_{s_i} = 0 \text{ if } i \notin \mathbb{A} \text{ (the admissible set).} \end{aligned} \tag{6}$$

The counterfactual TFP-max (optimal) subsidies. Reallocating the subsidy budget among all firms to maximize TFP leads to an increase of 2.22% relative to the structural allocation by subsidizing 262 firms out of 1,413 (top panel of Table 3). I exploit the data on applicants for subsidy grants to reallocate the subsidies among the 431 applicants, which results in an improvement in TFP of 1.02%. This stark decrease in the potential of the policy by simply restricting the admissible set highlights the importance of eligibility criteria or firm self-selection when designing policy in the real world. The reallocation of subsidies among applicants is implementable because, arguably, any applicant could receive a subsidy if the policymaker decided to do so. Admittedly, subsidizing non-applicant firms may require additional efforts such as information campaigns or may be prohibited by regulations of supranational authorities such as the EU or the World Trade Organization. Restricting the admissible set further to the 349 actual recipients diminishes the potential further to a 0.81% gain in TFP. If the policy-maker had chosen the participant firms among the applicants to maximize TFP, reducing the admissible set from applicants to participants would leave the TFP-maximum unchanged. Indeed, applicants are a random draw from the population of firms in terms of TFPR, as are the participants (Figure 1). In contrast, to maximize TFP, as Section V.3 shows, subsidies should go to high-TFPR firms.

The bottom panel of Table 3 presents results from the same exercise on a model with only capital distortions. The importance of the admissible set in driving the policy's potential is reflected in those results, too. Reallocating subsidies among applicants materializes only 41% of the potential TFP gains (in the baseline model, the equivalent quantity is 46%).

Table 3: Main results II: Bounds on the potential effect of subsidies on TFP.

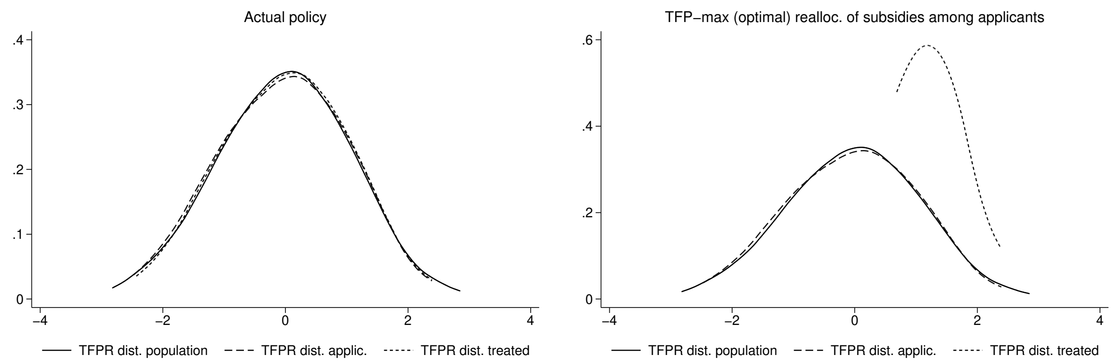
	TFP-min subsidies			Actual	TFP-max subsidies		
	Reallocate among:			subsidy	Reallocate among:		
	All	App.	Partic.	policy	Partic.	App.	All
	Baseline model with output and capital distortions						
ΔTFP from *struct.* $\widehat{\mathbf{TFP}}$ %	-3.55	-1.81	-1.40	-0.15	0.81	1.02	2.22
Rank reversals (size=L)*	4.88	1.49	0.85	10.97	4.46	5.87	12.10
Rank reversals (size=K)	3.89	1.06	0.42	19.25	7.22	9.70	22.15
# firms in adm. set $\mathbb{A}$	1,413	431	349	431	349	431	1,413
# treated firms	37	16	11	349	82	104	262
Decomposition of ΔTFP-max from *struct.* $\widehat{\mathbf{TFP}}$ %[†]					36	46	100
	Alternative model with only capital distortions						
ΔTFP from *struct.* $\widehat{\mathbf{TFP}}$ %	-5.88	-2.62	-1.84	-0.44	0.33	0.44	1.09
# treated firms	7	4	10	349	77	107	387
Decomposition of ΔTFP-max from *struct.* $\widehat{\mathbf{TFP}}$ %[†]					30	41	100
	Cost of public funds[‡] as a % of aggregate output						
Estimated range				[0.08 – 0.45]			
Midpoint of range				0.27			

The table compares the allocation under various policies to the structural allocation. All policies are subject to the same budget constraint $\mathbf{K}_s/\mathbf{K} \leq 2.8\%$. The numbers reported are percentage deviations of a statistic X under a policy from the same statistic under the structural allocation $\hat{X}$—i.e., $100 \times (X/\hat{X} - 1)$.
*The reversals in ranking statistics show the percent of firms whose rank in the firm size distribution—measured by the decile in which they reside—changed because of the policy. Size is measured by a firm's employment or its capital.
†This line decomposes the improvement in TFP that the TFP-max policy brings over the no-subsidies counterfactual into three components: (1) the increase from reallocating the resources among the subsidized firms only; (2) the increase from reallocating the resources among the firms that applied for a subsidy; and (3) the increase from reallocating the resources among the universe of firms in the dataset, which by construction is 100%.

But in the alternative model the changes in TFP are smaller because, in part, the structural TFP is closer to the efficient one in models with capital-only distortions (Table 2). And therefore, there is not as much room for improvement as in a model with two types of distortions.

The counterfactual TFP-min (worst-case) subsidies. Reallocating the subsidy budget among all firms to maximize TFP leads to its decrease by 3.55% relative to the structural allocation by subsidizing 37 firms out of the 1,413 eligible ones (top panel of Table 3). Reallocating the subsidies among either applicants or participants can decrease TFP by at least 1% (-1.81 and -1.40%, respectively). The calculated potential negative effect of the policy on TFP is as large using the alternative model with a single type of distortion (-5.88,

Figure 1: Who is applying and who is treated? Conditioning on $\widehat{\text{TFPR}}$



-2.62, and -1.84% in the bottom panel of Table 3). It appears that it is easier to massively exacerbate misallocation than moderately mitigate it because the same budget could lead to at least twice a decrease in TFP than an increase.

The cost of public funds. To evaluate whether the TFP-maximizing policies are worth pursuing, one needs to take into account potential deadweight losses generated from raising funds for financing the policy through distortionary taxes; such deadweight loss is what public economists call the cost of public funds. Since the policy's effect is expressed in terms of yearly output while the policy's budget as a fraction of the aggregate capital stock, the budget needs to be transformed into a yearly flow in terms of output. I do so by using the flow cost of capital 2.8%RK and the implication of the Cobb-Douglass production function that the expenditure on capital is a fraction of output $\alpha\mathbf{Y}$. That reasoning brings the policy's budget to 0.98% of output, which is in line with the 1.26% of GDP the EU spends in capital transfers and a bit larger than the 0.5% aid to the non-agricultural and non-financial sector (see the online appendix). Using estimates from the public finance literature on the cost of public funds ranging from 9 to 50 cents for every dollar raised, I calculate the cost of public funds of this policy between 0.08 and 0.45 percent of output with a midpoint at 0.27% (last lines of Table 3). The midpoint estimate implies that all three TFP-maximizing policies using either the baseline or the alternative model increase output even after taking into account the cost of public funds. Even at the upper bound of the cost of public funds, all baseline TFP-maximizing policies increase output. The online appendix includes the details of calculating these bounds.

Reversals of firm rank in the size distribution. Why are the potential effects of discretionary policies that large? It is because of their power to change the allocation of resources markedly. Hopenhayn (2014) formalizes this argument by showing that policies that preserve the rank of firms in the firm size distribution, such as size-dependent policies, are unlikely to have significant effects on the aggregate TFP. In contrast, discretionary subsidy policies can change the rank of firms in the size distribution. Indeed, the actual policy moves 19.97–19.25% of firms across deciles, depending on whether employment or capital signifies firm size. (Table 3). Similarly, under the TFP-max subsidy policy, 12.10–22.15% of firms changed decile. Interestingly, as the admissible set $\mathbb{A}$ expands, the TFP gains and the share of firms moving across deciles increase. That co-movement reflects that the more power the policy has to transform the size distribution, the higher the potential TFP gains are.

Robustness. The main results are robust to performing the analysis at the 2-digit industry level using either the baseline or the alternative model. In sum, the actual policy decreases TFP in at least 3/4 of the industries but, still, it performs better than the uniform in 85% of them. The uniform reduces TFP in 92% and 100% of the industries under the baseline and alternative model, respectively. The policy upper bound boosts TFP by 1–2%, and reallocating subsidies among applicants realizes 1/3 of the potential TFP gains in the median industry. The lower bound is several percentage points and 3–4% in the median industry depending on the specification.

V.3 Firm-level analysis

This section analyzes the extensive margin—that is, the probabilities of being subsidized (treated). The online appendix presents an analysis of the intensive margin—that is, the subsidy rate of the treated firms.

I first explore which firms receive a subsidy under the optimal subsidy policy. To do so, I run a set of univariate logit models of the probability of receiving a subsidy (to being treated) for a list of predictor variables Z. The focus of the exercise to determine which variables can best predict the TFP-maximizing set of treated firms; therefore, the main takeaway from each regression is the pseudo R^2, which in likelihood estimators is a measure of model fit. Table 4 presents the results of the maximum likelihood estimation of the logit models, where each row is a different model characterized by its single explanatory variable. The first three variables are the ones that, according to our theoretical analysis and

Table 4: Firm-level analysis: Treatment probability for TFP-max and actual policies

	Univariate Logit prob($\tilde{\tau}_s > 0 \vert Z$) models						
	Optimal policy			Actual policy			
Explanatory var. Z	Coef. β	S.E.	Model fit Pseudo R^2	Coef. β	S.E.	Model fit Pseudo R^2	Correlation $\log \widehat{TFPR}$, Z
$\log \widehat{TFPR}$	11.43	1.11	0.81	0.01	0.06	≈0	1.00
$\log \frac{1}{1-\tau_{Yi}}$ §	2.28	0.12	0.40	0.31	0.06	0.02	0.75
$\log \widehat{\text{MRPK}}$ *	1.64	0.09	0.26	-0.27	0.06	0.01	0.80
$\log(1 + \hat{\tau}_{Ki})$	0.48	0.06	0.04	-0.43	0.06	0.03	0.42
Firm characteristics as predictors							
$\log A_i$(TFPQ)	1.57	0.09	0.25	0.34	0.06	0.02	0.69
$\log \hat{K}_i$ (size)†	-0.30	0.06	0.01	0.53	0.06	0.05	-0.23
log Age‡	-0.07	0.07	≈0	-0.05	0.06	≈0	-0.06
Observations	1,413			1,413			
Subsidized firms	262 (18.5%)			349 (24.7%)			

All variables are calculated under the structural allocation in the economy $\{1-\tau_{Yi}, 1+\hat{\tau}_{Ki}, A_i\}_i$ and are standardized by taking logs, then subtracting the median and, finally, dividing by the standard deviation. The standard errors (S.E.) are heteroskedasticity robust.

§ The output wedge $\frac{1}{1-\tau_{Yi}}$ is proportional to the structural marginal product of labor $\widehat{\text{MRPL}}$ and is the common component of the $\widehat{\text{MRPK}}$ and $\widehat{\text{MRPL}}$.

* The $\widehat{\text{MRPK}}$ is calculated as $\frac{1+\hat{\tau}_{Ki}}{1-\tau_{Yi}}$.

† The size variable is the capital stock under the structural allocation and is calculated using the formula in (2).

‡ For each firm, age is considered the number of years since the firm's establishment plus one, which implies that in the year of establishment, the firm is one-year old. For the analysis, Age_i is the average age of each firm in the dataset.

simulations in Section III.4.1, matter—namely, the capital wedge $1 + \hat{\tau}_K$, the MRPK, and the TFPR. For comparability of coefficients among models, the variables are standardized by taking logs, then subtracting the median and, finally, dividing by the standard deviation. All variables are calculated under the structural allocation in the economy $\{1 - \tau_{Yi}, 1 + \hat{\tau}_{Ki}, A_i\}_i$— the allocation where there is no subsidy policy, factual, optimal, or otherwise. This allocation is the reference point because, from the viewpoint of this paper, there is an economy facing structural misallocation and the goal is to evaluate the effect of various policies on this economy. Hence, the starting point for any policy is the structural allocation. The takeaway from Table 4 is that the TFPR is the variable with the highest predictive ability, reflected in a pseudo R^2 of 0.81. The logit coefficient of 11.43, if exponentiated, denotes how the odds of being subsidized change as the TFPR changes. In particular, the odds of receiving a subsidy for a firm with TFPR one standard deviation above the median are 90,000 times higher[22] than the odds of a firm with TFPR at the median of the TFPR distribution– an enormous difference in odds.

Since the ability of the TFPR to predict treatment is so large, the last column of the table presents the correlation between the log TFPR and the other predictor variables because, arguably, variables that are highly correlated with TFPR are likely to be good predictors of treatment. Indeed, the output wedge $1/(1-\tau_Y)$ and the MRPK, which are highly correlated with the TFPR, are good predictors of treatment with pseudo R^2 of 0.40 and 0.26, respectively—good predictors but not nearly as good as the TFPR. The capital wedge $1+\hat{\tau}_K$, which, in the data, is reflected in the firm's labor-capital ratio, has low predictive ability with an R^2 of 0.04. The ranking in the predictive power of the TFPR, the MRPK, and the capital wedge is consistent with the simulation results in the online appendix.

The next set of variables does not represent distortions in the model but may be indicators of distortions according to findings from other datasets analyzed in the literature. One particular variable that has attracted considerable attention in the literature is firm-productivity A_i (TFPQ). This is because TFPQ is found to be correlated with measures of distortions, in the sense that firms with high TFPQ tend to have higher MRPK or higher output distortion τ_Y (and, hence, higher MRPL).[23] For instance, the correlation between the MRPK and TFPQ for China (see Hsieh and Klenow, 2009, Table A.1) is 0.59, while in this dataset, it is 0.44—of the same sign and similar magnitude. Bento and Restuccia (2017) study the correlation between firm productivity and distortions using a one-factor production function (abstracting from capital) and data from 62 countries; they find that the correlation between firm labor productivity and an output distortion ranges from 0.22 to 0.74. Even though, their model does not map directly to mine, their correlation is closely related to the correlation between log TFPQ and log MRPL or between log TFPQ and log TFPR, which in this dataset are 0.64 and 0.69, respectively. After establishing that, indeed, the correlations between distortions and firm productivity in this dataset are positive and consistent with the literature, I turn to the estimated coefficient of TFPQ in the logit model in Table 4, which is 1.57. This number implies that the odds of receiving a subsidy for

[22] The exponential exp(11.43) is approximately equal to 90,000.

[23] A reason behind such a correlation might be size-dependent policies that are favorable to small firms but penalize large firms. High-TFPQ firms should be large at the efficient allocation, but size-dependent policies may force them to settle for a suboptimal size. Garicano et al. (2016) show how in the French regulatory environment, which becomes more stringent for firms with more than 49 employees, can be represented as large firms facing a 2.3 percent higher labor taxation than small firms. In my framework, such a labor tax would show up in the TFPR measure.

a firm with TFPQ one standard deviation above the median are 4.8 times higher[24] than the odds of a firm with TFPQ at the median of the TFPQ distribution. Therefore, because of this positive relationship between firm productivity and distortions (whether they are measured by MRPK, MRPL, or TFPR), under the optimal policy, higher TFPQ firms are considerably more likely to be subsidized than lower TFPQ firms.

I now turn to describing the predictive ability of two additional firm characteristics that may be indicators of distortions: firm size and age. Hadlock and Pierce (2010) show empirically that financially-constrained firms are likely to be young and small, and, therefore, such constraints may prevent firms from acquiring the efficient level of resources. If the TFPR reflects some of these constraints, then it is likely that size and age can predict treatment under the optimal policy. Indeed, the negative correlation between the TFPR and size or age is negative, albeit small. Consistent with these negative correlations, the optimal policy is more likely to subsidize small or young firms; but the effect is small and the pseudo R^2 of both logit models is nearly zero.

Correlated distortions. Interestingly, under the optimal policy, firms with high capital distortions $\hat{\tau}_K$ are not much more likely to be treated than firms with low capital distortions. This is surprising because high capital distortions imply that firms face high constraints in acquiring capital. Nonetheless, the capital distortion $\hat{\tau}_K$ is not the only source causing firms to acquire lower capital than in the efficient allocation, as both the output distortion and the capital distortion are responsible for the wedge in the marginal product of capital $MRPK \propto \frac{1+\hat{\tau}_K}{1-\tau_Y}$. A policy aiming to maximize TFP in an economy with distortions—reflected in the allocation of both capital and labor—puts a lot of weight on firms using too little labor and capital, which is reflected in the output wedge $1-\tau_Y$ affecting both the MRPK and the MRPL. This is the reason that the output wedge has high predictive power over treatment. In addition, the correlation between the output and the capital wedge in the data is negative and equal to -0.28, implying that firms that are overall constrained face a lower capital distortion that is reflected in a low labor capital ratio L/K relative to other firms.[25] The analysis of the extensive margin below describes how the capital distortion gains importance when considering the magnitude of subsidy rates among treated firms. Thus, the correlation structure of the *structural* distortions is crucial for the design and evaluation of policy interventions.

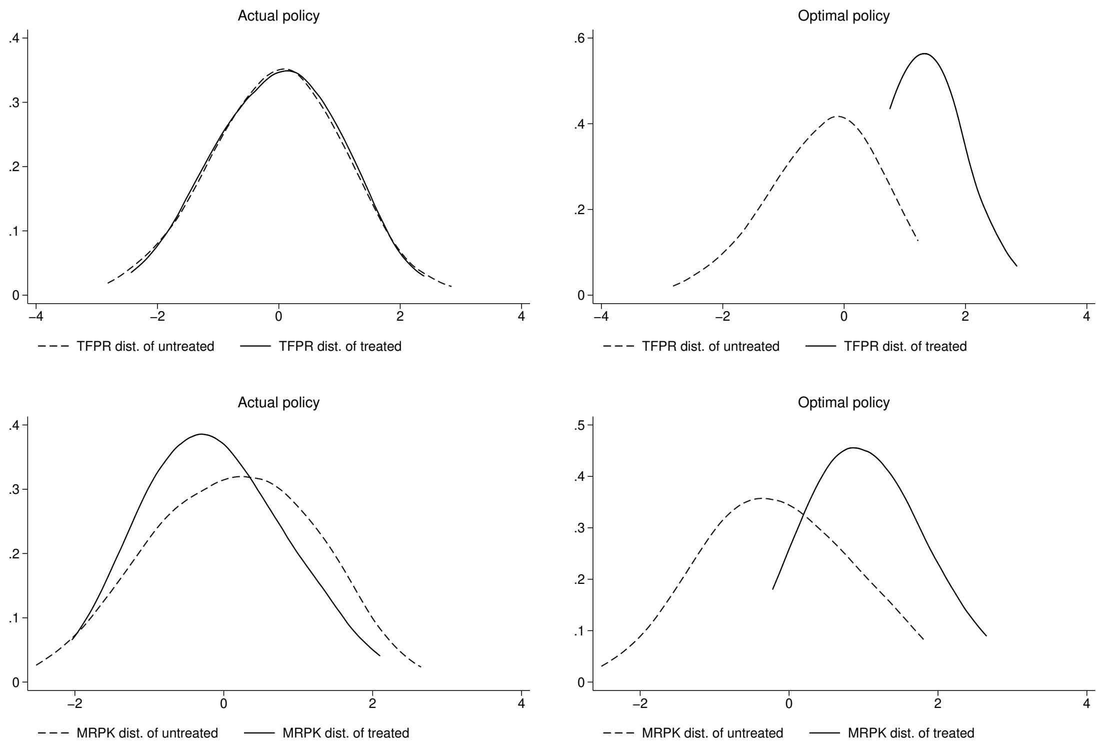
[24] The exponential exp(1.57) is approximately equal to 4.8.

[25] For the complete correlation matrix of distortions and firm characteristics, see the online appendix.

The treatment probability under the actual and optimal policies. To explore why the actual policy decreases the aggregate TFP while the optimal policy increases it, I compare the characteristics of the treated firms under the two policies—the extensive margin of the policies—by running the same set of logit models run for the optimal policy, for the actual one as well. The results from the logit models run for the optimal and the actual policy are side by side in Table 4. The main finding is that, unlike under the optimal policy, under the actual policy, resources are not directed to firms with high TFPR. Instead, it appears that low-TFPR firms are as likely to be treated as high-TFPR firms, which is reflected in the nearly zero estimated coefficient of the TFPR in the logit model in Table 4. To further explore the characteristics of treated firms under the optimal and actual policies, The top left panel of Figure 2 plots the TFPR distribution of treated firms against the TFPR distribution of untreated firms under the actual policy. The two distributions look identical, implying that it is as if treated firms are selected at random from the population. In stark contrast, the top right panel shows that, under the optimal policy, the TFPR distribution of treated firms is positioned on the right of the distribution of the untreated firms, and the two distributions barely overlap. This remarkable difference between the two policies is the main reason behind their disparate impact on the aggregate TFP.

I now compare treated and untreated firms in terms of characteristics beyond the TFPR. While the second-best predictor of treatment under the optimal policy is the output wedge $\frac{1}{1-\tau_Y}$, this variable has low predictive power over treatment under the actual policy. Nonetheless, the actual policy is more likely to subsidize firms with high output distortions, in line with the optimal. In terms of the MRPK, whereas the optimal policy is more likely to treat high-MRPK firms, the actual policy is more likely to subsidize low-MRPK firms. This is evident in the second row of Figure 2, which shows that the MRPK distribution of treated firms lies to the left of the distribution of untreated firms under the actual policy but to the right under the optimal policy. Regarding the capital wedge $1 + \hat{\tau}_K$, the results from the logit model in Table 4 show that, although firms with a large capital wedge are more likely to be treated under the the optimal policy, they are less likely to be treated under the actual policy. In terms of size, the optimal policy is less likely to treat large firms, while the actual policy is more likely to subsidize large firms. With respect to age, neither the actual nor the optimal policy favors firms of a particular age regarding treatment. The firm-specific productivity TFPQ is one of the firm characteristics that is a good predictor for treatment under the optimal policy even though it is not directly related related to measures of misallocation. This predictive power of the TFPQ is, instead, related to the

Figure 2: Actual vs. optimal policy: Treated and untreated firms



empirical fact, common among many datasets, that TFPQ is highly correlated with TFPR, which is the main misallocation indicator. In line with the optimal policy, the actual policy is more likely to treat firms with high TFPQ, but the relationship between treatment and TFPQ is much weaker in the actual policy versus the optimal. In sum, even though the actual policy is more likely to treat high-productivity firms, the relationship between treatment probability and productivity is not strong enough to result in TFP gains.

VI Concluding remarks

In an effort to understand the causes and potential remedies of misallocation, this paper studies the impact of discretionary capital subsidies on TFP. Using a model featuring firm-specific distortions and data from Greek manufacturing that includes information on firm-specific subsidies, it finds that subsidies decreased TFP by 0.15%. The model allows for calculating bounds on the potential effects of any policy, which depend on the joint distribution of existing distortions and firm-specific productivity and the policy's budget. Such policy bounds are useful for ex-ante policy evaluation as they give a sense of the best- and the worst-case scenario. They can also be used for ex-post policy evaluation to determine where within the possible outcomes an actual policy stands. Also, the analytical framework provides a tool for policy design as it allows for calculating TFP-maximizing subsidies given existing distortions in the capital, labor, and output markets. In this dataset, a TFP-maximizing policy should subsidize firms with high productivity (TFPQ), which is driven by the positive empirical relationship between distortions and TFPQ in this dataset, like in many other datasets studied in the literature. Unfortunately, selecting firms into the policy based on the observable firm characteristics of size or age is unlikely to improve TFP.

One general result coming out of the analysis is that discretionary subsidies with budgets similar in size to the ones spent by developed or developing countries can have large effects on TFP (several percentage points) and, therefore, are worth exploring as a potential source of misallocation. The analytical framework allows for a variety of counterfactuals that reallocate subsidies among different sets of firms. I use that feature to show that reallocating subsidies only among firms who applied for one realizes less than half of the potential TFP gains from a well-designed policy that redistributes subsidies among all firms. That result suggests that eligibility criteria or firm self-selection can be crucial for the successful design of policies. An appealing feature of the model is that it features heterogeneous treatment effects of subsidies, which is consistent with the empirical literature. An implication of the heterogeneity of responses by firms to subsidies is that a uniform subsidy is likely to decrease TFP because least-constrained firms capitalize more on the availability of subsidized inputs. That insight calls attention to potential unintended consequences of the textbook industrial policy that advocates for sector-specific subsidies.

References

Adamopoulos, T., L. Brandt, J. Leight, and D. Restuccia (2017). Misallocation, selection and productivity: A quantitative analysis with panel data from China. *University of Toronto working paper 593*. 6, 28, 29

Aghion, P., J. Cai, M. Dewatripont, L. Du, A. Harrison, and P. Legros (2015). Industrial policy and competition. *American Economic Journal: Macroeconomics 7*(4), 1–32. 2, 8

Asker, J., A. Collard-Wexler, and J. De Loecker (2014). Dynamic inputs and resource (mis)allocation. *Journal of Political Economy 122*(5), 1013–1063. 6, 29

Asker, J., A. Collard-Wexler, and J. De Loecker (2019). (mis)allocation, market power, and global oil extraction. *American Economic Review 109*(4), 1568–1615. 7

Bartelme, D. G., A. Costinot, D. Donaldson, and A. Rodríguez-Clare (2019). The textbook case for industrial policy: Theory meets data. *NBER working paper 26193*. 5, 7, 19

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2013). Cross-country differences in productivity: The role of allocation and selection. *American Economic Review 103*(1), 305–34. 6

Bartik, T. J. (2019). Should place-based jobs policies be used to help distressed communities? *Upjohn Institute working paper 19-308*. 2

Barwick, P. J., M. Kalouptsidi, and N. B. Zahur (2019). China's industrial policy: An empirical evaluation. *NBER working paper 26075*. 7

Becker, S. O., P. H. Egger, and M. Von Ehrlich (2010). Going nuts: The effect of eu structural funds on regional performance. *Journal of Public Economics 94*(9-10), 578–590. 1

Bento, P. and D. Restuccia (2017). Misallocation, establishment size, and productivity. *American Economic Journal: Macroeconomics 9*(3), 267–303. 6, 38

Bils, M., P. J. Klenow, and C. Ruane (2020). Misallocation or mismeasurement? *NBER working paper No. 26711*. 6, 28

Boehm, J. and E. Oberfield (2018). Misallocation in the market for inputs: Enforcement and the organization of production. *NBER working paper 24937*. 6

Busso, M., J. Gregory, and P. Kline (2013). Assessing the incidence and efficiency of a prominent place based policy. *American Economic Review 103*(2), 897–947. 1

Chen, Z., Z. Liu, J. C. Suárez Serrato, and D. Xu (2016, November). Notching r&d investment with corporate income tax cuts in china. Mimeo. 5, 18

Criscuolo, C., R. Martin, H. G. Overman, and J. Van Reenen (2019). Some causal effects of an industrial policy. *American Economic Review 109*(1), 48–85. 8

David, J. M., H. A. Hopenhayn, and V. Venkateswaran (2016). Information, misallocation and aggregate productivity. *Quarterly Journal of Economics 131*(2), 943–1005. 6

David, J. M. and V. Venkateswaran (2019). The sources of capital misallocation. *American Economic Review 109*(7), 2531–2567. 3, 6, 22, 29, 31

David, J. M., V. Venkateswaran, A. P. Cusolito, and T. Didier (2019). Capital allocation in developing countries. *World Bank working paper*. 6

Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015). The next generation of the Penn World Table. *American Economic Review 105*(10), 3150–82. 25

Garicano, L., C. Lelarge, and J. Van Reenen (2016). Firm size distortions and the productivity distribution: Evidence from France. *American Economic Review 106*(11), 3439–79. 15, 38

Gopinath, G., Ş. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez (2017). Capital allocation and productivity in south Europe. *The Quarterly Journal of Economics 132*(4), 1915–1967. 5, 6, 16, 19, 24

Hadlock, C. J. and J. R. Pierce (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies 23*(5), 1909–1940. 39

Heckman, J. J. (2000). Causal parameters and policy analysis in economics: A twentieth century retrospective. *The Quarterly Journal of Economics 115*(1), 45–97. 14

Heckman, J. J. and E. J. Vytlacil (2007). Econometric evaluation of social programs, part I: Causal models, structural models and econometric policy evaluation. In J. J. Heckman and E. E. Leamer (Eds.), *Handbook of Econometrics*, Volume 6B, pp. 4779–4874. Elsevier. 14

Hopenhayn, H. A. (2014). On the measure of distortions. *NBER working paper 20404*. 6, 36

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics 124*(4), 1403–1448. 2, 3, 4, 5, 6, 8, 10, 19, 24, 28, 30, 38

Hurwicz, L. (1966). On the structural form of interdependent systems. In *Studies in Logic and the Foundations of Mathematics*, Volume 44, pp. 232–239. Elsevier. 14

Itskhoki, O. and B. Moll (2019). Optimal development policies with financial frictions. *Econometrica 87*(1), 139–173. 7

Jones, C. I. (2016). The facts of economic growth. In J. Taylor and H. Uhlig (Eds.), *Handbook of Macroeconomics*, Volume 2, pp. 3–69. Elsevier. 8

Kalemli-Ozcan, S., B. Sorensen, C. Villegas-Sanchez, V. Volosovych, and S. Yesiltas (2015). How to construct nationally representative firm level data from the ORBIS global database. *NBER working paper No. 21558*. 23

Kalouptsidi, M. (2018). Detection and impact of industrial subsidies: The case of Chinese shipbuilding. *The Review of Economic Studies 85*(2), 1111–1158. 7

Kline, P. and E. Moretti (2014). People, places, and public policy: Some simple welfare economics of local economic development programs. *Annual Review of Economics*. 1

Krugman, P. (2018). Making tariffs corrupt again. *The New York Times, September 20*. 2

Lashkaripour, A. and V. Lugovskyy (2019). Scale economies and the structure of trade and industrial policy. *mimeo Indiana University*. 7

Marschak, J. (1953). Economic measurements for policy and prediction. In W. C. Hood and T. C. Koopmans (Eds.), *Studies in Econometric Method*, pp. 1–26. Cowles Commission for Research in Economics. 14

Midrigan, V. and D. Y. Xu (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review 104*(2), 422–458. 6

Oberfield, E. (2013). Productivity and misallocation during a crisis: Evidence from the chilean crisis of 1982. *Review of Economic Dynamics 16*(1), 100–119. 6

OECD (2010). *Roundtable on Competition, State Aids and Subsidies*. Paris: Organisation for Economic Co-operation and Development, Competition Committee, Global Forum on Competition. DAF/COMP/GF(2010)5. 2

Papaioannou, F. (2010). The effect of the changes in investment incentives in greece on national and regional economic growth. Thesis, The University of Thessaly. In Greek. 8

Ramey, V. A. and M. D. Shapiro (2001). Displaced capital: A study of aerospace plant closings. *Journal of Political Economy 109*(5), 958–992. 27

Restuccia, D. and R. Rogerson (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics 11*(4), 707–720. 5, 19

Restuccia, D. and R. Rogerson (2013). Misallocation and productivity. *Review of Economic Dynamics 1*(16), 1–10. 6

Restuccia, D. and R. Rogerson (2017). The causes and costs of misallocation. *Journal of Economic Perspectives 31*(3), 151–74. 5, 6, 17

Rodrik, D. (2008). Normalizing industrial policy. *World Bank, Washington, DC*. 15, 19

Slattery, C. (2020). Bidding for firms: Subsidy competition in the u.s. *Columbia University working paper*. 8

Slattery, C. R. and O. M. Zidar (2020). Evaluating state and local business incentives. *Journal of Economic Perspectives 34*(2), 90–118. 8

Tankersley, J. (2018a). Chinese metals win U.S. tariff waivers with little resistance. *The New York Times, November 28*. 2

Tankersley, J. (2018b). Steel giants with ties to Trump officials block tariff relief for hundreds of firms. *The New York Times, August 5*. 2

Zwick, E. and J. Mahon (2017). Tax policy and heterogeneous investment behavior. *American Economic Review 107*(1), 217–48. 5, 18