



ABSTRACT

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Nel complesso panorama dell'economia, l'allocatione efficiente delle risorse è una forza fondamentale che determina la produttività, l'innovazione e la crescita a lungo termine. Questa tesi esplora i modi in cui le distorsioni in questo processo di allocatione, spesso sottili ma pervasive, influenzano il modo in cui le economie rispondono alle politiche, alle opportunità tecnologiche e agli shock esterni. Attraverso una serie di indagini interconnesse che spaziano dalla politica regionale in Europa, alle decisioni di innovazione a livello aziendale, alle vulnerabilità strutturali dell'agricoltura ai cambiamenti climatici, la tesi esplora un tema unificante: le distorsioni non sono solo un ostacolo statico all'efficienza, ma anche un argomento di riflessione nella progettazione delle politiche economiche. Il percorso di questa ricerca si è sviluppato organicamente durante il mio dottorato di ricerca, riflettendo una progressione da applicazioni empiriche orientate alle politiche a quadri teorici che collegano il livello micro con le implicazioni macroeconomiche. È iniziato con l'articolo congiunto "Structural Funds and Regional Convergence: The Role of Resource Misallocation", con Massimo Del Gatto ("Università G. d'Annunzio, LUISS e CRENOSS") e Mattia Peracchia ("Università G. d'Annunzio"), un'analisi dei trasferimenti di coesione dell'UE e della convergenza regionale utilizzando un panel NUTS-2 delle regioni europee per il periodo 1995-2022 tratto dal database ARDECO, combinato con i pagamenti della politica di coesione e un approccio sistemico con regressioni a minimi quadrati in tre fasi, variabili strumentali e dati panel per valutare il ruolo dei fondi nel determinare l'allocatione errata e la convergenza regionale. I dati indicano un doppio meccanismo: sebbene vi sia un effetto diretto e i trasferimenti riducano direttamente i divari di PIL pro capite, essi aumentano anche la misallocatione a livello regionale; il canale distorsivo indiretto compensa parzialmente (e in alcune aree prevale) l'effetto di convergenza diretto, con una forte eterogeneità tra macroregioni e settori. Questo focus iniziale si è naturalmente evoluto in un'esplorazione più approfondita delle distorsioni, passando dall'analisi a livello regionale a un approccio più diretto e a una misurazione più accurata attraverso l'uso di microdati, utilizzati per comprendere le distorsioni del capitale a livello di impresa, incorporando un modello di imprese eterogenee ispirato alla letteratura sul commercio e sulla concorrenza di qualità, arricchito con microdati per verificare le previsioni sugli incentivi all'innovazione e gli esperimenti empirici aggregati. A questo proposito, nel secondo articolo, "Firm-Level Capital Misallocation as a Brake on Innovation", scritto con Massimo Del Gatto, abbiamo combinato le decisioni di innovazione e le distorsioni a livello di impresa. In primo luogo, verifichiamo le implicazioni del modello attraverso un modello a ostacoli, poi esaminiamo le relazioni empiriche aggregate. Ciò che emerge è un ruolo negativo significativo della misallocatione sull'innovazione da un lato e un ruolo negativo dei sussidi all'innovazione in contesti di misallocatione dall'altro. A livello aggregato, l'eliminazione della relazione sistematica tra misallocatione e produttività genera, all'interno del modello, guadagni tecnologici medi di circa il 15%. A seguito di questa evoluzione, e grazie al mio coinvolgimento in un progetto di ricerca sui legami tra allocatione errata e agricoltura, ho trascorso sei mesi come studente ospite presso il Dipartimento di Economia dell'Università di Toronto, dove la mia ricerca si è ulteriormente evoluta in direzione della trasformazione strutturale e dell'economia dello sviluppo. In questo modo, il terzo saggio, scritto in collaborazione con Tasso Adamopoulos ("York University"), Hyungju Henry Kim ("OCSE"), Duc Nguyen ("Amherst College") e Diego Restuccia ("Università di Toronto") intitolato "Farm Size, Climate Adaptation, and Unequal Climate Damages across Countries", indaga sul perché shock climatici simili generino conseguenze economiche molto diverse tra i vari paesi. Sosteniamo che la distribuzione delle dimensioni delle aziende agricole sia un determinante strutturale chiave della capacità di adattamento. Combinando prove microeconomiche sull'adozione di tecnologie con un modello di equilibrio generale caratterizzato da aziende agricole eterogenee e adattamento endogeno, il documento mostra che le economie dominate da piccole aziende agricole investono meno nella mitigazione dei cambiamenti climatici, subiscono maggiori perdite di produttività agricola e subiscono inversioni più marcate nella trasformazione strutturale, portando a aumenti sostanziali dell'insicurezza alimentare. Questi risultati implicano che i cambiamenti climatici possono ampliare i divari di reddito tra i paesi anche in presenza di shock comuni, attraverso meccanismi radicati nella struttura agricola piuttosto che nella sola geografia. Nel loro insieme, questi saggi riflettono un progressivo approfondimento sia dal punto di vista empirico che metodologico. L'analisi passa dalla valutazione delle politiche regionali al comportamento a livello di impresa e, infine, a una prospettiva di equilibrio generale, con ogni capitolo che si basa su quello precedente in termini di dettaglio dei dati, impostazione econometrica e integrazione teorica. Nel corso di questa progressione, il lavoro passa da relazioni in forma ridotta ad approcci più strutturalmente fondati che collegano i meccanismi microeconomici ai risultati aggregati. Nel loro insieme, i tre capitoli offrono prospettive complementari sui legami tra politica, comportamento delle imprese e sviluppo economico.



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Abstract (max 10.000 characters)

In the complex landscape of economics, efficient resource allocation is a fundamental force that determines productivity, innovation, and long-term growth. This thesis explores the ways in which distortions in this allocation process, often subtle but pervasive, influence how economies respond to policies, technological opportunities, and external shocks. Through a series of interconnected investigations spanning regional policy in Europe, innovation decisions at the firm level, and the structural vulnerabilities of agriculture to climate change, it explores a unifying theme: distortions are not only a static obstacle to efficiency, but also a topic for reflection in economic policy design. The path of this research developed organically during my PhD, reflecting a progression from policy-oriented empirical applications to theoretical frameworks linking the micro level with macroeconomic implications. It began with the joint article "Structural Funds and Regional Convergence: The Role of Resource Misallocation," with Massimo Del Gatto ("G. d'Annunzio University, LUISS and CRENOS") and Mattia Peracchia ("G. d'Annunzio University"), an analysis of EU cohesion transfers and regional convergence using a NUTS-2 panel of European regions for the period 1995-2022 drawn from the ARDECO database, combined with cohesion policy payments and a systemic approach with three-stage least squares regressions, instrumental variables, and panel data to assess the role of funds in determining misallocation and regional convergence. The data indicate a dual mechanism: while there is a direct effect and transfers directly reduce per capita GDP gaps, they also increase misallocation at the regional level, the indirect distortionary channel partially offsetting (and in some areas dominating) the direct convergence effect, with strong heterogeneity across macro-regions and sectors. This initial focus has naturally evolved into a more in-depth exploration of distortions, moving from regional-level analysis to a more direct approach and more accurate measurement through the use of microdata, used to understand capital distortions at the firm level, incorporating a model of heterogeneous firms inspired by the literature on trade and quality competition, enriched with microdata to test predictions about innovation incentives and aggregate empirical experiments. In this regard, in the second article, "Firm-Level Capital Misallocation as a Brake on Innovation," with Massimo Del Gatto, we combined innovation decisions and distortions at the firm level. First, we test the implications of the model through an obstacle model, then we look at the aggregate empirical relationships. What emerges is a significant negative role of misallocation on innovation on the one hand and a negative role of innovation subsidies in contexts of misallocation on the other. At the aggregate level, removing the systematic relationship between misallocation and productivity generates, within the model, average technological gains of about 15%. Following this evolution, and thanks to my involvement in a research project on the links between misallocation and agriculture, I spent six months as a visiting student at the Department of Economics at the University of Toronto, where my research further evolved in the direction of structural transformation and development economics. On this way, the third essay, joined with Tasso Adamopolous ("York University"), Hyungju Henry Kim ("OECD"), Duc Nguyen ("Amherst College") and Diego Restuccia ("University of Toronto") entitled "Farm Size, Climate Adaptation, and Unequal Climate Damages across Countries", investigates why similar climate shocks generate vastly different economic consequences across countries. We argue that the distribution of farm size is a key structural determinant of adaptation capacity. Combining micro evidence on technology adoption with a general equilibrium model featuring heterogeneous farms and endogenous adaptation, the paper shows that economies dominated by small farms invest less in climate mitigation, experience larger agricultural productivity losses, and undergo stronger reversals in structural transformation, leading to substantial increases in food insecurity. These results imply that climate change can widen cross-country income gaps even under common shocks, through mechanisms rooted in agricultural structure rather than geography alone. Taken together, these essays reflect a gradual expansion in both empirical depth and methodological structure. The analysis moves from regional policy evaluation to firm-level behavior and, ultimately, to a general equilibrium perspective, with each chapter building on the previous one in terms of data detail, econometric design, and theoretical integration. Over the course of this progression, the work shifts from reduced-form relationships toward more structurally grounded approaches that link microeconomic mechanisms to aggregate outcomes. Together, the three chapters offer complementary perspectives on the links between policy, firm behavior, and economic development.



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XXXVIII Cycle

Essays on Misallocation, Innovation and Economic Development

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Essays on Misallocation, Innovation, and Economic Development

Introduction

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Structural Funds and Regional Convergence: The Role of Misallocation

A joint work with Massimo Del Gatto and Mattia Peracchia

Abstract

We study the effect of EU structural funds on regional convergence in Europe, accounting for misallocation as a transmission channel. Using NUTS-2 data over 2000–2022, we estimate Three-Stage Least Squares linking funds, misallocation, and income gaps with respect to the frontier. We find a dual mechanism: EU funds directly reduce income gaps, but also indirectly increase misallocation, which in turn widens them. In aggregate, the direct effect dominates, although the indirect distortionary channel partially offsets these gains. The two effects vary along the gap distribution. In regions far from the frontier, transfers promote convergence through capital accumulation, while misallocation slows catching-up. Closer to the frontier, where growth relies more on productivity, transfers are less effective and may generate divergence, while misallocation reduces the gap through a compression of growth in more productive regions. Misallocation therefore operates as a constraint on European regional convergence and reduces the effectiveness of EU structural funds in narrowing regional income gaps.

Keywords: Regional Convergence, Misallocation, EU Structural Policy, Cohesion Funds

JEL Codes: R11, R58, O47, O52, H54

1 Introduction

Since its creation, the European Union has placed economic cohesion at the center of its integration project, devoting substantial policy effort and financial resources to reducing territorial disparities and promoting convergence across member states and regions. Yet, a striking empirical pattern complicates this picture: over the period 2000–2022, the standard deviation of real GDP per-capita across EU regions has been rising—indicating σ -divergence—even as EU regions exhibit evidence of β -convergence. This apparent contradiction, driven primarily by heterogeneous dynamics across the distribution of regional income gaps, suggests that aggregate convergence measures may mask offsetting mechanisms operating through different channels. Understanding which channels are at work is therefore essential for evaluating the effectiveness of cohesion policy.

A key reason for these conflicting dynamics, we argue, is misallocation, the inefficient allocation of capital and labor across regions, whereby inputs are not directed toward their most productive uses. In an efficient economy, factors flow freely across locations until their marginal products are equalized; persistent deviations from this condition signal the presence of distortions. Following Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), such distortions can generate sizable losses in aggregate productivity. Crucially, large-scale transfers of public funds can themselves alter the spatial allocation of resources: if structural funds redirect capital and labor toward regions or uses where their marginal productivity is relatively low, they may inadvertently widen allocative distortions, generating an indirect divergence channel that partially offsets their direct redistributive effect. This channel has been overlooked by the existing literature on EU cohesion policy and regional convergence.

We document a set of empirical patterns that motivate this mechanism. EU structural funds have been increasing over time, yet σ -divergence has been rising. Moreover, our measure of regional misallocation tracks the evolution of EU transfers closely, rising after periods of intense funding and stabilizing when transfers moderate. These patterns suggest that the effectiveness of cohesion transfers may depend critically on whether they exacerbate or mitigate allocative distortions across regions.

We then estimate a system of equations in which misallocation depends on EU structural funds, and the regional GDP per-capita gap depends on both misallocation and EU funds. This allows us to disentangle the indirect effect of transfers operating through allocative distortions from their direct effect on convergence. The system is estimated by Three-Stage Least Squares (3SLS) with region and year fixed effects, using a harmonized panel of NUTS-2 regional data covering 26 EU countries over the period 2000–2022, drawn from the ARDECO database and the EU Cohesion Policy Open Data Portal. Identification relies on an instrumental-variable strategy based on eligibility thresholds for cohesion funding, following Becker et al. (2010).

The aggregate results deliver two main findings. First, EU funds exert a direct convergence-enhancing effect on regional income gaps: transfers reduce the GDP per-capita gap between recipient regions and the productivity frontier. Second, EU funds simultaneously increase the extent of regional misallocation, and higher misallocation in turn widens income gaps, generating an indirect divergence channel that partially offsets the direct redistributive effect.

In a detailed view, we find a mixed effect across the quartiles of the income gap distribution. In particular, in less developed regions, capital accumulation promotes convergence, although this is hindered by misallocation. Instead, in regions not far from

the frontier, misallocation narrows the gap by reducing the growth rate of the frontier. In general, misallocation acts asymmetrically over the gap distribution, affecting capital accumulation in regions far from the frontier and productivity in more advanced areas.

Thus, our paper relates to two main strands of literature. First, it connects to the large empirical literature on EU structural funds and regional convergence (Boldrin and Canova (2001), Becker et al. (2010), Becker (2012), Esposti and Bussoletti (2008), Montresor et al. (2010), Fiaschi et al. (2011)). Despite the large and long-standing empirical literature on EU structural funds and regional convergence, a clear and universally shared consensus has yet to emerge. Studies employing different methodologies, programming periods, types of funds, and measures of convergence have produced highly heterogeneous and often contradictory results. We contribute to this debate by identifying misallocation as a previously overlooked transmission channel. Through this channel, cohesion transfers may simultaneously promote convergence directly while undermining it indirectly, thereby offering a unified explanation for the mixed and often conflicting evidence in the literature.

Second, the paper connects to the literature on misallocation and aggregate productivity (Restuccia and Rogerson (2008), Hsieh and Klenow (2009)). This literature has emphasized how factor market distortions generate large productivity losses at the firm and industry level. We contribute by bringing this framework to the regional level and showing that policy-driven transfers can themselves be a source of allocative distortions, with quantitatively relevant consequences for convergence dynamics.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 introduces the framework used to measure regional misallocation. Section 4 describes the data sources and variables definition. Section 5 offers a preliminary graphical investigation of the key patterns. Section 6 presents the empirical strategy and results. Section 8 concludes.

2 Background Literature

The inconclusive evidence surveyed in the introduction motivates a better examination of the two strands of literature that underpin our analysis: the empirical work on regional convergence and the role of European structural funds, and the theoretical and empirical literature on misallocation. We review each in turn, before discussing the more recent contributions that connect subsidies directly to allocative distortions.

2.1 European Funds and Economic Convergence

The literature on regional convergence distinguishes between β -convergence, the tendency of poorer regions to grow faster than richer ones, and σ -convergence, a reduction in the cross-sectional dispersion of per-capita income (Sala-i Martin (1996)). Quah (1996) showed, however, that average-based measures can conceal substantial persistence in the income distribution and the formation of distinct convergence clubs. From these two seminal contributions, the literature has devoted considerable efforts to first examining convergence in Europe and then, given the Union's goal of internal cohesion, to understanding the relationship between subsidies and their effectiveness in achieving that goal, without reaching a common result.

Systematic reviews show that convergence is frequently treated as a spillover of growth or conflated with aggregate economic performance rather than analyzed as a distinct

outcome [Mockevičienė and Butkus \(2026\)](#). A meta-analysis of 323 estimates from 17 studies confirms that funds exert a positive effect on regional growth, yet this effect is highly heterogeneous and depends on methodology, programming period, fund type, and regional characteristics [Dall’Erba and Fang \(2017\)](#).

Empirical studies have examined both β -convergence and σ -convergence, as well as club convergence. Most analysis focus on Objective 1 (the least developed regions with GDP per-capita below 75% of the EU average), although more recent work distinguishes between the European Regional Development Fund (ERDF) and the European Social Fund (ESF) or examines total Structural Funds across the 1989–2013 and 2014–2020 programming periods. This heterogeneity partly reflects differences in empirical design and measurement. Existing studies vary in whether they identify average treatment effects, exploit eligibility discontinuities, compare alternative programming periods, or measure treatment intensity through funds per capita or as a share of regional GDP.

Empirical findings differ sharply across approaches. Several contributions report positive growth effects, especially in Objective 1 regions. [Puigcerver-Peñalver \(2007\)](#) finds a significant impact of Structural Funds on GDP per worker between 1989 and 1999, particularly when supported by human capital and private investment. Moderate but positive effects, often stronger in regions with higher administrative capacity and better institutions, are documented by [Becker et al. \(2010\)](#) and [Becker \(2012\)](#). Similarly, [Goecke and Hüther \(2016\)](#) shows that EU regional subsidies increase the probability of convergence when allocated to areas with a robust industrial base and directed toward manufacturing, transport, and environmental planning.

At the same time, a substantial body of research presents more cautious or even negative assessments. Early spatial econometric studies detect β -convergence across 145 EU regions between 1989 and 1999 but find no statistically significant impact of the funds once inter-regional spillovers and endogeneity are accounted for [Dall’Erba and Le Gallo \(2008\)](#). In this sense [Boldrin and Canova \(2001\)](#) argue that European funds have neither induced structural transformation nor sustained productivity growth. [Esposti and Bussolletti \(2008\)](#) find no evidence that Objective 1 funds led to conditional convergence in the 1989–2004 period, while [Montresor et al. \(2010\)](#) and [Fiaschi et al. \(2011\)](#) document negative or null effects for funds not directed to convergence objectives.

More recent evidence further qualifies these contrasting results. Regression discontinuity designs applied to Objective 1 regions establish a causal positive effect on per-capita GDP growth, with impacts ranging between 1.2 and 1.8 percentage points annually depending on the programming period [Becker et al. \(2018\)](#). The returns, however, are strongly conditional on absorptive capacity and institutional quality [Becker et al. \(2018\)](#), [Rodríguez-Pose and Fratesi \(2004\)](#) that argue that only human-capital investments generate robust medium-term growth; infrastructure and business-support spending show weak or null effects [Rodríguez-Pose and Fratesi \(2004\)](#). Dynamic local-projection analysis shows that the ERDF produces positive short-term effects on output, investment and employment that dissipate within three years, while the ESF exerts insignificant short-term effects but economically meaningful positive medium-term effects [Canova and Pappa \(2025\)](#). Macro-model simulations for the 2014–2020 period confirm that the funds reduce territorial disparities, particularly in less-developed regions [Crucitti et al. \(2024\)](#).

A common message emerging from this evidence is that the effect of cohesion policy is highly heterogeneous. Aggregate convergence remains elusive, and distinct convergence clubs persist along a North-West versus South-East divide [Borsi and Metiu \(2015\)](#). Even when funds support convergence on average, their effects vary with regional character-

istics, including urban–rural structure, distance to large agglomerations, local territorial capital, and national implementation models [Maynou et al. \(2016\)](#); [Gagliardi and Percoco \(2017\)](#); [Bachtrögl et al. \(2020\)](#); [Crescenzi and Giua \(2020\)](#). This heterogeneity is also evident in studies of treatment intensity. Extending the RDD framework to continuous treatment, [Cerqua and Pellegrini \(2018\)](#) show that the relationship between Structural Funds and growth is concave: after a certain threshold, additional transfers generate sharply diminishing returns. This evidence suggests that the effectiveness of cohesion policy depends not only on whether regions receive funds, but also on how intensively they are treated and on whether additional resources are absorbed efficiently.

Taken together, these contributions confirm that EU Cohesion Policy generates positive yet highly conditional effects on regional growth and convergence. The magnitude, persistence, and spatial distribution of these effects vary markedly with transfer intensity, local territorial capital, and national implementation models. The persistent lack of consensus in the literature underscores the importance of investigating the specific channels that may limit the effectiveness of the funds. One critical channel is the misallocation of resources: when regions fail to allocate Structural Funds efficiently, they are unable to use them to their full potential. This inefficiency can substantially weaken the funds’ capacity to stimulate growth and, ultimately, to achieve their primary objective of promoting regional convergence.

2.2 Subsidies and Misallocation

A growing literature shows that subsidies and place-based transfers can affect not only the level of economic activity, but also the allocation of resources across firms, sectors, and regions. When public support is not aligned with marginal productivity, it may sustain low-productivity units, distort factor allocation, and weaken aggregate productivity. This mechanism is central for evaluating cohesion policy, since transfers intended to reduce regional disparities may also alter the efficiency with which resources are allocated across space. Evidence from firm-level studies supports this view. [Byrne and Goodhead \(2025\)](#) examine capital misallocation across manufacturing firms in 19 European countries and show that firm-specific distortions, including subsidies, account for a substantial part of productivity differences across European regions. Related evidence from China reaches a similar conclusion: [Jin \(2018\)](#) shows that government subsidies can increase resource misallocation and reduce manufacturing productivity. In the European context, [Fattorini et al. \(2020\)](#) provide a more nuanced picture for ERDF support. Broad business support has little effect on firm competitiveness, whereas targeted support for product and process innovation raises TFP, especially among initially low-productivity firms. Taken together, these studies indicate that the productivity effects of public support depend critically on whether transfers relax productive constraints or instead distort the allocation of resources. Evidence from agriculture points in the same direction. [Rizov et al. \(2013\)](#) show that Common Agricultural Policy subsidies had a negative effect on farm productivity before the decoupling reform, while their effect became more heterogeneous afterward. They interpret this pattern as the net result of two opposing forces: productivity gains induced by investment and productivity losses generated by allocative and technical inefficiencies. [Morando and Newman \(2022\)](#) provide direct evidence on this second channel, showing that farm-specific subsidies can generate capital misallocation and sizable aggregate productivity losses. These findings are useful for our setting because they show that subsidy programs may simultaneously support production and distort the allocation

of inputs, making their aggregate effect depend on the balance between investment and misallocation channels.

Taken together, this evidence suggests that subsidies can affect productivity not only by changing the level of investment, but also by changing the allocation of resources across production units. Two mechanisms are particularly relevant for cohesion policy.

First, public transfers may weaken selection and distort targeting. If support is not aligned with marginal productivity, it can allow low-productivity firms, sectors, or regions to expand or survive, while resources are prevented from moving toward more productive uses. Consistent with this mechanism, [Herrera et al. \(2022\)](#) show that industrial policy in China increased TFPR dispersion in targeted industries by directing larger subsidies and lower taxes toward low-TFPR firms, while imposing relatively higher taxes on high-TFPR firms. Second, place-based transfers may affect local factor prices. By increasing demand for labor, land, capital, or non-tradable inputs in recipient areas, subsidies can generate wedges between marginal products and factor costs and thereby increase spatial dispersion in revenue productivity. This mechanism is closely related to the spatial-equilibrium logic in [Kline and Moretti \(2014\)](#), where local transfers are capitalized into wages and rents and therefore alter the incidence and efficiency effects of place-based policy.

These mechanisms imply that transfers designed to promote convergence may also reduce allocative efficiency. Our contribution is to examine this trade-off in the context of EU cohesion policy, estimating whether structural funds reduce regional income gaps directly while simultaneously increasing misallocation and weakening their overall convergence effect.

3 Misallocation

In order to measure misallocation at the regional level, we adopt a [Hsieh and Klenow \(2009\)](#) framework in which misallocation is measured by examining the dispersion of the marginal revenue product (MRP) of inputs (marginal product times output price), specifically capital and labor, across regions.

In an ideal economy with frictionless factor markets, firms equalize the MRP of each factor to its nominal cost (economic efficiency condition). With all firms located in a given region bearing the same factor cost, the MRP is equalized across firms and the average (in the region) MRP of each factor equals its factor cost. With firm in different EU regions facing the same factor cost, the MRP is equalized across also regions and the average (across regions) MRP of each factor equals its factor cost.

Deviations from this ideal economic efficiency condition indicate the presence of misallocation, entailing the coexistence of regions exhibiting a MRP higher than the average, using a “too low” amount of inputs, and regions exhibiting a MRP lower than the average, using a “too high” amount of inputs. The observed dispersion in factors’ MRPs across regions therefore signals out distortions in the allocation of resources.

Formally, the production function for region r at time t in sector s can be expressed as:

$$Y_{rst} = A_{rst} K_{rst}^{\alpha_{st}} L_{rst}^{1-\alpha_{st}} \quad (1)$$

where Y_{rst} is output, K_{rst} and L_{rst} are capital and labor respectively. α and $(1 - \alpha)$ are, respectively, the factor shares for capital and labor, which are assumed to be sector-

year specific. The term A_{rst} , denoting the Hicks-neutral TFP component, can be written as

$$TFP_{rst} \equiv A_{rst} = \frac{Y_{rst}}{K_{rst}^{\alpha_{st}} L_{rst}^{1-\alpha_{st}}} \quad (2)$$

With its revenue-based equivalent (i.e., TFPR – Revenue Total Factor Productivity) defined as:

$$TFPR_{rst} \equiv P_{rst} A_{rst} = \frac{P_{rst} Y_{rst}}{K_{rst}^{\alpha_{st}} L_{rst}^{1-\alpha_{st}}} \quad (3)$$

where P_{rst} is the average price set at time t by sector s firms located in region r , at time t .

Profit maximization yields the economic efficiency condition according to which the MRP of each factor (i.e., capital and labor) equals its cost ($\omega_{rst}^K, \omega_{rst}^L$)¹:

$$MRPK_{ist} \equiv \alpha_{st} \frac{Y_{ist}}{K_{ist}} = \omega_{st}^K \quad \text{and} \quad MRPL_{ist} \equiv (1 - \alpha_{st}) \frac{Y_{ist}}{L_{ist}} = \omega_{st}^L. \quad (4)$$

Under the hypothesis that EU factor markets are fully efficient and integrated, EU firms operating in a given sector face the same factor cost, entailing the sector-year MRP of each factor be the same across EU regions and, as a consequence, equal to its average value (i.e., $MRPL_{rst} = \overline{MRPL}_{st} \forall r \in EU$). However, if firm-specific inefficiencies (i.e., wedges) are present, the above first-order conditions yield:

$$MRPK_{rst} = \omega_{st}^K (1 + \tau_{rst}^K) \quad \text{and} \quad MRPL_{rst} = \omega_{st}^L (1 + \tau_{rst}^L). \quad (5)$$

where τ_{rst}^K and τ_{rst}^L subsume the distortions in capital and labor markets, respectively. Cross-firm and cross-region heterogeneity in these wedges prevents firms/regions from operating under the economic efficiency condition, thereby determining an inefficient allocation of inputs which materializes in terms of MRP dispersion: the larger the dispersion, the larger is the inefficiency. In this context, within-EU dispersion in regional MRP can be understood as measuring the extent of market frictions/inefficiencies in EU factor markets, preventing the cross-region allocation from being the most efficient.

Hsieh and Klenow (2009) show that quite standard model assumptions yield proportionality between MRP and $TFPR$. In other words, MRP equalization implies TFPR equalization, entailing that TFPR dispersion can be used, instead of MRP dispersion, to quantify the extent of factor market frictions.

A further caveat concerns what TFPR dispersion captures beyond misallocation per se. As shown by Asker et al. (2014) and Haltiwanger (2016), TFPR dispersion can reflect adjustment costs in factor markets, markup heterogeneity across regions or sectors, or demand-side differences in output markets, none of which necessarily constitute misallocation in the allocative efficiency sense.

In our regional setting, where TFPR is constructed from region-level aggregates rather than firm-level data. As a result, the measure reflects average revenue productivity at the regional level. While this aggregation may attenuate idiosyncratic firm-level heterogeneity, it does not eliminate systematic differences in markups, adjustment costs or demand

¹Intuitively, in a frictionless environment, firms expand by attracting additional inputs until their MRPs (given the assumption of decreasing MP) are driven down to the common factor prices. This process continues until no firm can increase profits by adjusting its input bundle, which occurs precisely when $TFPR$ is equalized across firms.

conditions across regions. To the extent that these factors vary geographically, they may contribute to the observed dispersion and affect the estimated coefficients. ²

4 Data and variables definition

The analysis relies on databases that combine economic, demographic, and financial information, ARDECO (Annual Regional Database of the European Commission) database, and granular information on the allocation and disbursement of European Union funds, the EU Cohesion Policy Open Data Portal³. These funds are important instruments used to promote economic, social, and territorial cohesion across member states and regions⁴. Although each fund has a specific purpose, they all contribute to reducing disparities and supporting development.

From ARDECO we rely on the compensation of employees at current prices, the Gross Fixed Capital Formation at current prices, the gross value added at basic prices. All of them are provided by industry. As well as, we acquire the real GDP per-capita and the implicit deflator. Instead, from EU Cohesion Policy Open Data Portal we rely on all EU funds provided which are not provided by industry, unfortunately.

First of all we consider the Cohesion Fund (CF), which is designed to support member states with lower income levels, finances environmental projects and transport infrastructure. In other words, its main aim is to reduce development gaps and promote more balanced growth across the EU. Focused on rural areas, the European Agricultural Fund for Rural Development (EAFRD) aims to improve the competitiveness of agriculture, encourage the sustainable management of natural resources, and support the economic and social development of rural communities. Also the maritime sector, indeed the European Maritime and Fisheries Fund (EMFF) was created to support fisheries, aquaculture, and coastal communities. Its purpose was to promote sustainable activities linked to the sea and to strengthen the resilience of these areas. One of the most important fund among the main tools of EU regional policy is the European Regional Development Fund (ERDF). It aims to reduce regional disparities and improve competitiveness, supporting investments in infrastructure, innovation, digitalization, and environmental transition. The European Social Fund (ESF) supports employment, education, training, and social inclusion, especially for groups facing difficulties in the labor market. Under EU cohesion policy, NUTS-2 regions are classified according to their level of development. The main convergence objective—historically known as Objective 1 (now called “less developed regions”)—targets the poorest regions, defined as those with GDP per-capita below 75% of the EU average at the start of each programming period. These regions receive the highest intensity of structural funds. In order to counter poverty, the Fund for European Aid to the Most Deprived (FEAD) provided basic material assistance, such as food and essential goods, while also promoting measures of social inclusion. Finally, a more targeted instrument was the Youth Employment Initiative (YEI), which was aimed at young people, especially those not in employment, education, or training. Its main

²Accordingly, our measure should be interpreted as a proxy for allocative inefficiency, capturing overall dispersion in revenue productivity across regions rather than isolating pure distortions in factor allocation.

³European Commission, Cohesion Open Data.

⁴Also EU candidate countries could receive financial supports before formal accession in the EU through pre-accession assistance instruments, aimed at preparing them for membership and alignment with EU rules and policies (European Commission, Pre-accession Assistance).

objective was to improve youth access to jobs, apprenticeships, traineeships, and training opportunities.

In cumulative terms, the ERDF and EAFRD together account for nearly 60% of total EU transfers, while the ESF represents around 20%, with the remaining funds—including CF, EMFF, FEAD, and YEI—covering the residual share. This distribution reflects the longstanding centrality of regional competitiveness and rural development in the EU’s cohesion agenda.

To better capture the actual timing of policy implementation and its potential economic effects, we rely on the “modelled annual expenditure” series. Moreover, we aggregate these annual expenditure from the different cohesion instruments in order to capture the total fiscal impulse received by each region (NUTS-2). Indeed, funds respond to different policy goals, ranging from infrastructure and competitiveness to rural development and social protection—they all contribute to shaping the regional economic landscape.

We conduct our analysis on a harmonized panel of regional (NUTS-2) data covering 26 EU countries over the period 2000–2022, United Kingdom included. The two missing countries are Ireland and Croatia. The former has been excluded because of problem related to the incompatibility association between the two databases we refer; the latter is excluded since it is available in the EU Cohesion Policy Open Data Portal from the year 2008 and for another reason that will be clear in a while.

Using the modelled annual expenditure series, that we deflate using the before mentioned deflator, we build our first variable (i.e., *EU Funds*). Moreover, we consider the real GDP per-capita (i.e., *GDPpc*) in order to construct our measure of distance to address the convergence issue (i.e., *GDPpc GAP*). In particular, we rely on the absolute distance from the real GDP per-capita frontier regions that we fix at the begin of the period (i.e., 2000)⁵. Specifically, we consider the difference between the average of the real GDP per-capita of the richest 5% of EU regions⁶ and the GDP per-capita of the given region (in a given year): $GDPpc\ Gap_{r,t} = \overline{GDPpc}_t^{5\%} - GDPpc_{r,t}$. This measure captures how far each region lies from the richest regions and provides a region-specific indicator of convergence dynamics over time, with a decreasing trend denoting convergence towards the frontier.

An important part of our analysis involve the construction of the *Misallocation* variable. In a perfectly efficient market, TFPR would be identical across all regions. However, Hsieh and Klenow (2009) show that MRP dispersion maps into TFPR dispersion, and that higher TFPR dispersion is, in turn, associated with more inefficient allocation and lower welfare (*misallocation*). If we use $TFPR_{r,t}$ to denote the TFPR of region r at time t and $\overline{TFPR}_t$ to denote the regional average, then $TFPR_{r,t}/\overline{TFPR}_t > 1$ implies that the region is inefficiently small and should be allocated more inputs in order to be able to increase its output and decrease its price until $TFPR_{r,t}/\overline{TFPR}_t = 1$. Conversely, $TFPR_{r,t}/\overline{TFPR}_t < 1$ implies that the region is inefficiently large and should be allocated less inputs in order to be able to decrease its output and increase its price. Since the region can be said to be inefficient in both cases, we measure the extent of misallocation across regions as the absolute value of the log deviation of regional TFPR from its annual

⁵Since our convergence measure fixes the countries at the starting period, Croatia will not be captured from our measure properly, so we exclude it.

⁶The 5% richest fixed regions at the starting period are, in order: Inner London, Outer London, Luxembourg, Brussels, Hamburg, Hovedstaden, Stockholm, Vienna, Île-de-France, the area Berkshire-Buckinghamshire-Oxfordshire, and Uusimaa.

mean:

$$Misallocation_{r,t} = \left| \ln \left(\frac{TFPR_{r,t}}{TFPR_t} \right) \right| \quad (6)$$

where $TFPR_{r,t}$ represents region-year revenue productivity weighted average for the sector's weight within the region. Specifically, the labor share (i.e., $(1 - \alpha_{s,t})$) is given by the average wage bill to value added ratio within each sector s - year t , and the capital share is obtained by complementarity. We perform the aggregation at the regional level because the funds are not sector-specific.

It is worth noting that, since $Misallocation_{r,t}$ is defined as an absolute deviation, a decrease in misallocation is consistent with different underlying reallocation patterns: resources may be flowing into a region that was previously under-allocated or out of a region that was over-allocated. Both dynamics reduce the absolute log deviation from the mean, yet they imply opposite directions of factor reallocation.

As a result, the measure captures the extent of dispersion around the efficient allocation, but does not identify the direction of adjustment. This feature has direct implications for the interpretation of the estimated coefficients: similar changes in the misallocation index may reflect different underlying economic mechanisms, which may contribute to the sign variation observed across specifications and subsamples depending on regions' initial positions relative to the efficiency frontier. Since EU funds are not allocated at the sectoral level in our data, all variables are collapsed at the regional level prior to estimation.

Descriptive statistics for the variables *Misallocation* and *EU Funds* are available in Table 1 and for *GDPpc* and *GDPpc GAP* in Table 2.

5 Preliminary Investigation

To better frame the investigation, in this section we present descriptive patterns covering the period 2000-2022. Namely, the time profile of EU cohesion funding, income disparities and factor misallocation are discussed. Figure 1 the evolution of the evolution standard deviation of the real GDP per-capita distribution (i.e., σ -convergence), β - convergence over the period 2000-2022, the total amount of EU funds that regions received and the mean of the misallocation (eq. 6).

First, we notice that there is a discrepancy between the σ - and β -convergence graph. It is clear that in the former the divergence of the real GDP per-capita had taken place, since the standard deviation shows that an upward trend along all entire period. However, the latter shows a different outcome: β -convergence had taken place. This confirms the different results we find in the literature. The other two graphs show the evolution of the overall amount of funds that regions received, and the evolution of the average misallocation. The former shows how the overall amount of EU funds allocated to EU regions has been increasing over time, with fluctuations mainly linked to the programming cycles of EU financial frameworks. Peaks in total funding are visible around 2013 and 2020, while the drop in 2016 reflects a well-known administrative transition between multi-annual programs. In the latter, the overall pattern shows that with the 2008 financial crisis, misallocation kept growing up to 2015 and next showing a downward trend. In the following sets of graphs we go into detail of each of these single graphs using the quartiles.

Figure 2 shows the evolution of the σ -convergence by quartile. In the first three quartiles, the σ -convergence shows an upward trend except for the last quartile, in which

the trend is stable over the entire period. In all these graphs, we can observe relevant drops in 2020. This is due to the fact that the UK officially left the European Union on 31 January 2020.

We compare the β -convergence of the quartiles with the border that we fix in the 2000-year in Figure 3. The frontier shows a light convergence, instead the regions in the first quartile show an important convergence towards the frontier, with a mass convergence range between 2% and 5%. For the second and third quartiles, we can see a slightly convergence, with several regions experiencing a negative growth and a more dispersion in the second quartile. Most of the regions in the last quartile show a convergence trend but with a more nuanced growth.

The evolution of the amount of funds for the quartiles (Figure 4) show an increasing trend for the regions in the first and the fourth quartiles, hence the regions at the extremes. Instead, regions which are around the median experienced a stable amount of funds.

Looking at the misallocation for each quartile in Figure 5, we can observe a slight upward evolution of the misallocation for the regions at the extremes of the distribution, an important upward trend in the period 2005-2016 for regions which are in the third quartile, and a stable trend for regions in the second quartile.

Together, these figures suggest an interaction between EU funds, regional misallocation, and convergence dynamics. In particular, the contrast between Figures 2 and 3 indicates that regions follow heterogeneous paths, with some converging towards the frontier while others diverge along the distribution of real GDP per-capita.

The apparent coexistence of σ -divergence and β -convergence is therefore not contradictory, but reflects differences in dynamics across the distribution. While β -convergence captures an average effect—where initially poorer regions grow faster— σ -divergence depends on the evolution of dispersion across all regions. As a result, overall variance may increase even when the most backward regions are catching-up, if intermediate regions move further away from the frontier.

These patterns point to the presence of heterogeneous responses along the income gap distribution, suggesting that convergence dynamics cannot be fully understood through aggregate measures alone. Instead, they motivate an analysis of the mechanisms operating across different segments of the distribution.

Consistent with this view, the evidence is in line with a framework in which the effects of transfers depend on underlying growth margins and vary with distance from the frontier. The next section builds on this intuition by identifying and quantifying the mechanisms at work.

6 Analysis

This section studies whether EU Structural Funds affect regional convergence directly and indirectly through their impact on allocative efficiency.

To account for the joint determination of transfers, misallocation, and convergence, we estimate the following system of equations:

$$Misallocation_{r,t-1} = \rho_0 + \beta_1 EU\ Funds_{r,t-2} + \delta GDPpc_{r,t-2} + \lambda_r + \lambda_t + \varepsilon_{r,t-1} \quad (7)$$

$$GDPpc\ GAP_{r,t} = \rho_1 + \gamma Misallocation_{r,t-1} + \beta_2 EU\ Funds_{r,t-1} + \lambda_r + \lambda_t + u_{r,t} \quad (8)$$

Region and year fixed effects are denoted by λ_r and λ_t , respectively. Moreover, all variables in the system of equations are expressed in logarithms.

The lag structure reflects institutional programming cycles and the gradual adjustment of production structures. More specifically, EU funds enter the misallocation equation with a two-period lag, $t - 2$, to reflect the time required for allocated resources to be absorbed and translated into changes in factor allocation. Given the multi-annual nature of EU programming cycles and the gradual implementation of funded projects, the effects of transfers on production structures are unlikely to materialize contemporaneously. Misallocation, in turn, enters the convergence equation with a one-period lag, $t - 1$, as allocative distortions affect income per capita through aggregate productivity, a mechanism that operates gradually as firms and regions adjust their input use. This staggered timing is intended to capture a sequential transmission from transfers to allocation and, subsequently, to convergence outcomes.

Misallocation appears both as an outcome and as a regressor, creating simultaneity and cross-equation correlation in the disturbances. For this reason, the system is estimated using a Three-Stage Least Squares (3SLS) approach, which jointly instruments endogenous regressors and exploits cross-equation covariance to improve efficiency relative to equation-by-equation IV estimation.

Following the quasi-experimental framework of [Becker et al. \(2010\)](#), identification exploits the institutional assignment rule governing Objective 1 status from the 2007–2013 programming period onward. Under EU Cohesion Policy, NUTS-2 regions whose GDP per-capita falls below 75% of the EU average qualify for preferential access to structural funds during the subsequent programming period. Because the threshold is centrally defined and based on pre-determined income conditions, it generates quasi-exogenous variation in access to EU funds across regions and programming cycles. For this reason, we map the sample into five programming periods: 1995–1999, 2000–2006, 2007–2013, 2014–2020, and 2021–2027. For each region r and programming period p , we construct a binary indicator $Eligibility_{r,p}$, which is constant within each period and captures whether the region qualifies for preferential treatment under the institutional rule. It is determined using pre-program income conditions. Specifically, for each region r , and period p , we compute the average $GDPpc$ of the region and of the EU over a reference window preceding the start of the programming period. Let $\mathcal{T}_p$ denote the corresponding pre-program years, we define:

$$\overline{GDPpc}_r^{pre,p} = \frac{1}{|\mathcal{T}_p|} \sum_{t \in \mathcal{T}_p} GDPpc_{r,t}, \quad \overline{GDPpc}_{EU}^{pre,p} = \frac{1}{|\mathcal{T}_p|} \sum_{t \in \mathcal{T}_p} GDPpc_{EU,t} \quad (9)$$

The eligibility is then given by:

$$Eligibility_{rp} = \mathbf{1} \{ \overline{GDPpc}_r^{pre,p} < 0.75 \overline{GDPpc}_{EU}^{pre,p} \} \quad (10)$$

The reference windows mirror the institutional assignment rule: 1997–1999 for the 2000–2006 period, 2004–2006 for 2007–2013, 2011–2013 for 2014–2020, and 2018–2020 for 2021–2027. For the initial 1995–1999 period, for which no three-year pre-window is available, eligibility is determined using GDP per-capita in 1995. ⁷

A potential concern is that eligibility is defined in terms of GDP per-capita relative to the EU average and is therefore mechanically related to the convergence outcome in the second equation of the system. Two considerations mitigate this concern. First,

⁷This follows the same institutional logic as in subsequent periods, in that eligibility is always based on income conditions predetermined with respect to the start of the programming period.

eligibility is determined using income conditions observed before the start of the relevant programming period, so it does not respond to contemporaneous shocks to convergence outcomes within the period. Second, the empirical specification includes region and year fixed effects, so identification relies on variation in access to EU funds induced by the institutional threshold across regions and programming cycles, rather than on persistent cross-sectional income differences per se. Accordingly, the exclusion restriction requires that, conditional on fixed effects and the lag structure, eligibility affects subsequent GDP per-capita gaps only through its impact on EU fund allocation. While this assumption cannot be tested directly, it follows the identification strategy in [Becker et al. \(2010\)](#) and is supported by the institutional nature of the assignment rule. Although eligibility confers preferential access to funding, actual transfers vary continuously and are not mechanically fixed by the rule. The assignment therefore induces a discrete increase in the expected intensity of EU transfers without perfectly determining funding levels. We exploit this institutional variation by using $Eligibility_{r,p}$ as an instrument for European funds in the first-stage equation:

$$EUFunds_{r,t} = \rho_0 + \rho_1 Eligibility_{r,p(t)} + \lambda_r + \lambda_t + \nu_{r,t} \quad (11)$$

In the second stage, predicted EU funds replace actual transfers in both the misallocation and $GDPpc$ equations. Within the 3SLS framework, the eligibility indicator instruments lagged EU funds, allowing us to identify both the *direct effect* of EU funds on $GDPpc$ GAP (β_2) and the *indirect effect* operating through misallocation ($\beta_1 \times \gamma$). Column (1) of Table [3](#) reports the benchmark 3SLS estimates, using the EU eligibility rule as an instrument for structural funds, as described in equation [11](#). The results indicate that structural funds increase regional misallocation, suggesting that larger transfers are associated with a less efficient allocation of resources across regions. Regional misallocation, in turn, increases the income gap with respect to the frontier, thereby slowing convergence. By contrast, structural funds have a direct negative effect on the income gap, indicating that transfers promote convergence once the indirect misallocation channel is accounted for.

Columns (2) and (3) report the corresponding panel fixed-effects estimates for the two equations estimated separately. The results are broadly consistent with the benchmark system estimates: structural funds increase regional misallocation, and structural funds directly reduce the income gap. The main difference is that the effect of regional misallocation on the income gap is not statistically significant when the convergence equation is estimated separately. The aggregate estimates identify the average transmission mechanism, but they do not explain why evidence of regional catch-up can coexist with rising dispersion across European regions. To investigate this issue, we allow the effects of structural funds and regional misallocation to vary across space and along the income-gap distribution. We first split the sample by broad European macro-regions, and then by quartiles of the distance from the frontier.

Table [4](#) estimates the benchmark 3SLS specification separately for Northern, Southern, and Eastern Europe.⁸ The results are consistent with the aggregate estimates. Across macro-regions, structural funds tend to increase regional misallocation, while their direct effect on the income gap remains convergence-enhancing. This confirms that the dual mechanism identified in the benchmark specification is not driven by a single European area.

⁸Countries are aggregated into macro-regions as follows. Northern Europe: AT, BE, FR, DE, SE, LU, NL, FI, DK, UK; Southern Europe: ES, IT, PT, CY, MT, EL; Eastern Europe: PL, CZ, SK, HU, RO, BG, EE, LV, SI.

Table 5 estimates the benchmark specification separately by quartiles of the income-gap distribution. The quartiles are constructed using each region's distance from the frontier. Regions in the first quartile are those closest to the frontier, while regions in the fourth quartile are those farthest from it. Thus, moving from the first to the fourth quartile corresponds to moving from relatively advanced regions to increasingly lagging regions.

The estimates reveal substantial heterogeneity along the distribution. In the first three quartiles, structural funds increase regional misallocation. However, the effects on the income gap differ sharply across quartiles. Among regions closest to the frontier, in the first and second quartiles, regional misallocation is associated with a lower income gap, while structural funds are associated with a higher income gap. In the third and fourth quartiles, the signs are reversed: regional misallocation increases the income gap, while structural funds reduce it.

In regions far from the frontier, capital scarcity implies high marginal returns to investment. Structural funds therefore operate mainly through capital accumulation and reduce the income gap, while regional misallocation weakens this channel by reducing the efficiency with which resources are allocated. Closer to the frontier, capital deepening plays a smaller role and growth depends more on productivity. In these regions, the positive coefficient of structural funds on the income gap suggests that transfers are less effective in generating productivity improvements. At the same time, the negative coefficient of regional misallocation should not be interpreted as evidence that misallocation improves convergence. Rather, it is consistent with a mechanical narrowing of the measured gap: regions close to the frontier may move closer to the benchmark because their relative performance weakens, not because resources are allocated more efficiently.

To quantify the relative importance of the two channels, Table 6 reports the direct, indirect, and total effects of structural funds, both in the full sample and by quartile of the income-gap distribution. The direct effect captures the impact of structural funds on the income gap that does not operate through regional misallocation. The indirect effect captures the transmission channel running from structural funds to regional misallocation and then from regional misallocation to the income gap. The total effect is the sum of these two components.

The decomposition confirms the main mechanism. In the full sample, the direct effect of structural funds is convergence-enhancing, while the indirect effect through regional misallocation works in the opposite direction. The total effect therefore depends on the relative strength of the productive and distortionary channels. Along the distribution, the balance between these channels changes. In regions far from the frontier, the direct convergence effect dominates, consistent with the role of capital accumulation in capital-scarce regions. In regions closer to the frontier, the direct effect is weaker or turns adverse, while the interpretation of the misallocation channel reflects the bad-convergence mechanism discussed above.

Tables 7 and 8 report the robustness analysis using only the Cohesion Fund and the European Regional Development Fund. The results confirm the direction and magnitude of the main coefficients. This indicates that the benchmark findings are not driven by the inclusion of funds outside the core instruments typically considered in the literature on cohesion policy and regional convergence.

Taken together, the empirical evidence indicates that EU structural funds operate through a dual transmission mechanism. On the one hand, transfers directly reduce regional income gaps. On the other hand, they increase regional misallocation, which

weakens convergence by lowering the efficiency with which capital and productive inputs are allocated across regions. The overall effect of cohesion policy therefore depends not only on the amount of resources transferred, but also on whether these resources reinforce productive accumulation or generate allocative distortions.

The heterogeneous results are consistent with a Solow-type interpretation of regional convergence. In regions far from the frontier, capital scarcity implies high marginal returns to investment. Structural funds are therefore more likely to foster convergence by supporting capital deepening. In these regions, misallocation works against convergence because it reduces the efficiency of the accumulation channel. Closer to the frontier, the scope for capital deepening is more limited and growth depends more on productivity improvements. In this part of the distribution, transfers are less effective if they fail to translate into productivity gains, while misallocation may reduce the measured gap through a deterioration of relative performance near the benchmark rather than through genuine catching-up.

The main implication is that the convergence effect of structural funds cannot be evaluated independently of their allocation effect. Transfers reduce regional income gaps when they support productive accumulation and productivity growth, but their impact is weakened when they increase misallocation. In this sense, misallocation acts as a constraint on the ability of cohesion policy to deliver economic convergence across European regions.

7 Conclusions

This paper examines the relationship between EU structural funds and regional convergence in Europe over the period 2000–2022, explicitly incorporating regional misallocation as a transmission channel. Rather than evaluating cohesion policy only through its redistributive dimension, we study how transfers interact with allocative efficiency and how this interaction shapes convergence dynamics.

Using a harmonized panel of NUTS-2 regions and a system of equations estimated by Three-Stage Least Squares with region and year fixed effects, we identify both the direct effect of structural funds on regional income gaps and the indirect effect operating through misallocation.

The results point to a dual transmission mechanism. Structural funds directly reduce income gaps with respect to the frontier, thereby promoting convergence. At the same time, they increase regional misallocation. Since higher misallocation widens income gaps in the aggregate, the indirect distortionary channel weakens the convergence effect of transfers.

The distributional results show that this mechanism is not uniform across regions. Moving away from the frontier, misallocation becomes increasingly harmful for convergence: where catching-up depends more on capital accumulation, allocative distortions reduce the efficiency of this channel and slow the narrowing of income gaps. The direct effect of structural funds follows the opposite logic. Transfers are less effective close to the frontier, where capital deepening plays a limited role and growth depends more on productivity improvements, but become more convergence-enhancing as capital scarcity increases. In this sense, the two channels operate in opposite directions along the distance from the frontier: the productive effect of funds is stronger where investment constraints are more binding, while the distortionary effect of misallocation is more damaging where

efficient accumulation is essential for catching-up.

These findings help rationalize the coexistence of β -convergence and σ -divergence. Poorer regions may catch up on average when structural funds support capital accumulation, while dispersion can still increase if misallocation slows convergence in lagging regions or if intermediate and relatively advanced regions fail to translate transfers into productivity growth. Aggregate convergence measures therefore mask important heterogeneity in the channels through which cohesion policy operates. Despite the use of lag structures, fixed effects, and a system estimator, a remaining limitation is that residual endogeneity and within-region heterogeneity cannot be fully ruled out with NUTS-2 data.

The main policy implication is that cohesion policy should be evaluated not only by the amount of resources transferred, but also by how those resources affect the allocation of capital and productive inputs across regions. Structural funds are more likely to promote convergence when they relax productive constraints and support capital deepening or productivity growth; their effectiveness is reduced when they generate allocative distortions. Improving the allocation of cohesion spending is therefore central to strengthening its long-run convergence impact.

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Table 1: Descriptive Statistics for Misallocation and EU Funds by Country.

	Misallocation (eq. (6))				EU Funds (mln EUR)			
	P25	Mean	P75	SD	P25	Mean	P75	SD
AT	0.05	0.09	0.13	0.05	28.45	60.94	79.46	46.06
BE	0.08	0.13	0.19	0.07	13.26	28.36	32.19	27.10
BG	0.06	0.16	0.25	0.12	19.90	117.36	176.28	102.77
CY	0.03	0.09	0.14	0.08	16.05	73.36	113.65	53.15
CZ	0.06	0.10	0.14	0.06	62.69	261.99	412.74	210.06
DE	0.03	0.08	0.11	0.06	33.62	106.33	104.41	135.17
DK	0.09	0.12	0.16	0.05	16.24	25.15	32.74	11.25
EE	0.13	0.18	0.23	0.08	176.00	390.43	631.22	251.96
EL	0.09	0.20	0.30	0.14	58.67	193.08	270.13	189.78
ES	0.05	0.12	0.17	0.08	58.11	312.01	395.41	371.86
FI	0.08	0.12	0.17	0.06	51.02	90.98	140.14	71.30
FR	0.08	0.12	0.15	0.05	63.66	106.59	133.33	59.15
HU	0.07	0.13	0.19	0.09	73.77	290.67	427.53	226.57
IT	0.04	0.10	0.15	0.08	52.19	230.02	234.61	300.70
LT	0.04	0.07	0.10	0.03	152.43	379.44	628.25	243.07
LU	0.17	0.22	0.27	0.07	13.56	20.80	24.53	11.64
LV	0.05	0.11	0.16	0.09	299.09	507.37	768.25	296.99
MT	0.04	0.09	0.11	0.06	16.35	69.92	108.17	56.21
NL	0.07	0.13	0.16	0.11	12.89	25.12	35.43	15.37
PL	0.04	0.10	0.14	0.07	115.71	423.14	654.39	353.38
PT	0.06	0.14	0.17	0.11	169.25	463.70	700.89	414.07
RO	0.11	0.23	0.34	0.13	28.51	253.76	407.18	207.92
SE	0.05	0.09	0.13	0.06	31.21	50.40	66.58	24.18
SI	0.04	0.09	0.13	0.06	0.00	124.86	253.62	162.67
SK	0.10	0.17	0.24	0.11	90.68	269.06	446.23	210.26
UK	0.03	0.06	0.09	0.03	26.30	56.27	63.95	60.36

Table 2: Descriptive Statistics for real GDP per-capita and GDP per-capita GAP by Country.

	Real GDP per-capita (EUR)				GDP per-capita gap (EUR)			
	P25	Mean	P75	SD	P25	Mean	P75	SD
AT	32572.00	38130.70	43430.00	7277.22	24338.00	30845.33	38138.70	9437.96
BE	25093.00	34518.84	38384.00	12846.54	30061.66	34847.03	45521.71	13400.58
BG	3836.00	5305.36	5805.00	2307.85	63641.55	63794.74	67100.66	6024.12
CY	21275.00	23197.26	24688.00	2219.74	46162.68	45902.84	49092.93	6622.09
CZ	11510.00	15169.09	14764.00	7254.39	54671.75	53931.01	59182.38	9327.90
DE	28246.00	34047.27	37986.00	8367.17	29542.09	35065.94	42415.66	10219.32
DK	38265.00	43907.62	46186.00	9643.82	17138.00	25707.15	32789.93	10156.47
EE	12854.00	14754.35	17369.00	2971.51	53734.55	54345.75	58528.47	7036.92
EL	13179.00	16018.76	18278.00	3662.21	49613.55	53081.34	56837.30	5542.11
ES	19243.00	22780.35	26404.00	4483.39	42187.90	46319.75	51120.59	6585.48
FI	33765.00	39976.16	47901.00	8162.75	20588.27	28880.05	36960.30	10037.50
FR	24665.00	26443.64	28726.00	7469.61	40490.93	42617.11	46496.00	9259.51
HU	6908.00	11887.61	10729.00	8927.55	51783.09	57212.49	63623.18	10733.18
IT	21059.00	28591.39	34060.00	7680.20	34370.00	40508.71	48675.71	8966.99
LT	20431.00	25961.61	32006.00	7371.13	39184.71	43138.49	51340.47	11065.92
LU	91227.00	94096.83	96755.00	4662.03	19455.53	24630.51	26289.42	8718.78
LV	9109.00	10707.26	12970.00	2646.15	57743.55	58392.84	61883.44	6773.37
MT	16336.00	20477.26	25088.00	4518.55	45461.71	48622.84	54388.66	8534.69
NL	30081.00	37014.12	43475.00	8210.07	24842.33	32132.42	40390.24	9978.56
PL	7047.00	9638.77	11037.00	3999.78	58893.55	59461.33	63576.44	7408.30
PT	15226.00	17444.45	18325.00	3183.69	48943.27	51655.64	55428.78	6055.45
RO	5644.50	7754.80	7554.00	4672.14	61807.55	61345.30	65290.22	7621.74
SE	36992.50	41693.90	42381.00	8164.21	24403.20	27652.81	33664.49	9468.45
SI	15391.00	18980.22	22252.00	4145.80	47474.55	50119.88	55511.93	7324.66
SK	9071.50	15573.98	17594.00	9525.96	44441.91	53526.12	61452.60	11355.71
UK	30334.00	42568.93	38361.50	39638.63	34526.48	40794.99	41353.45	26135.28

Figure 1: Overall graphs for σ -convergence (standard deviation of *real GDP per-capita*), β -convergence of the *real GDP per-capita*, *EU Structural funds*, and *Misallocation* (Eq. 6).

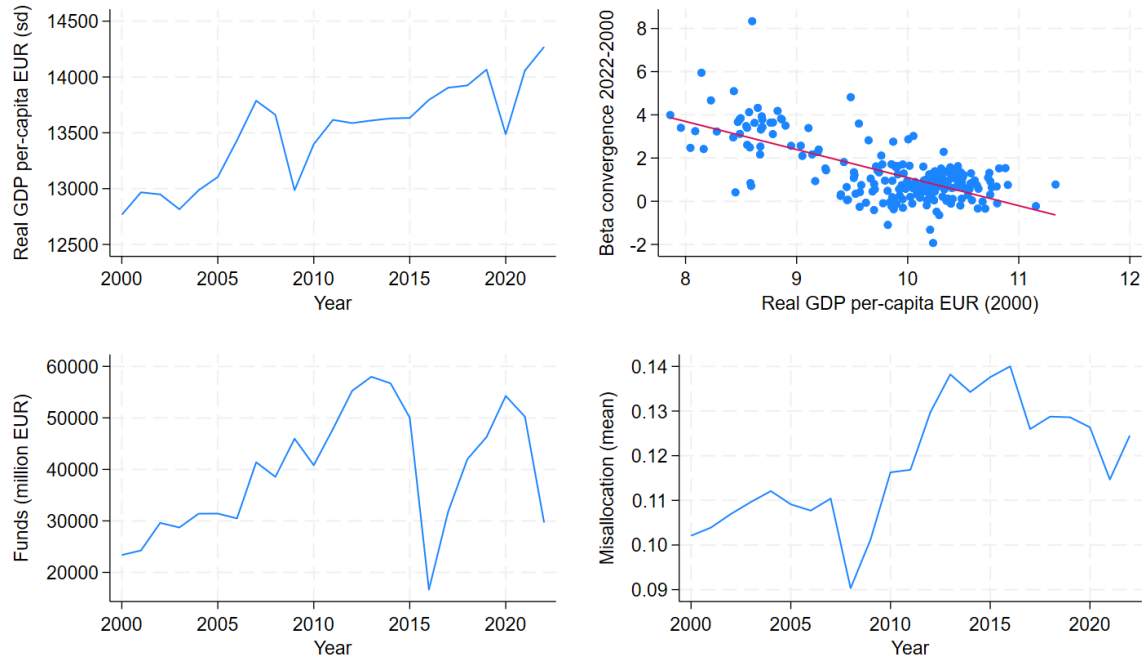


Figure 2: σ -convergence by quartile (standard deviation of *real GDP per-capita*).



Figure 3: β -convergence of real GDP per-capita by quartile keeping the border fixed along the distribution.

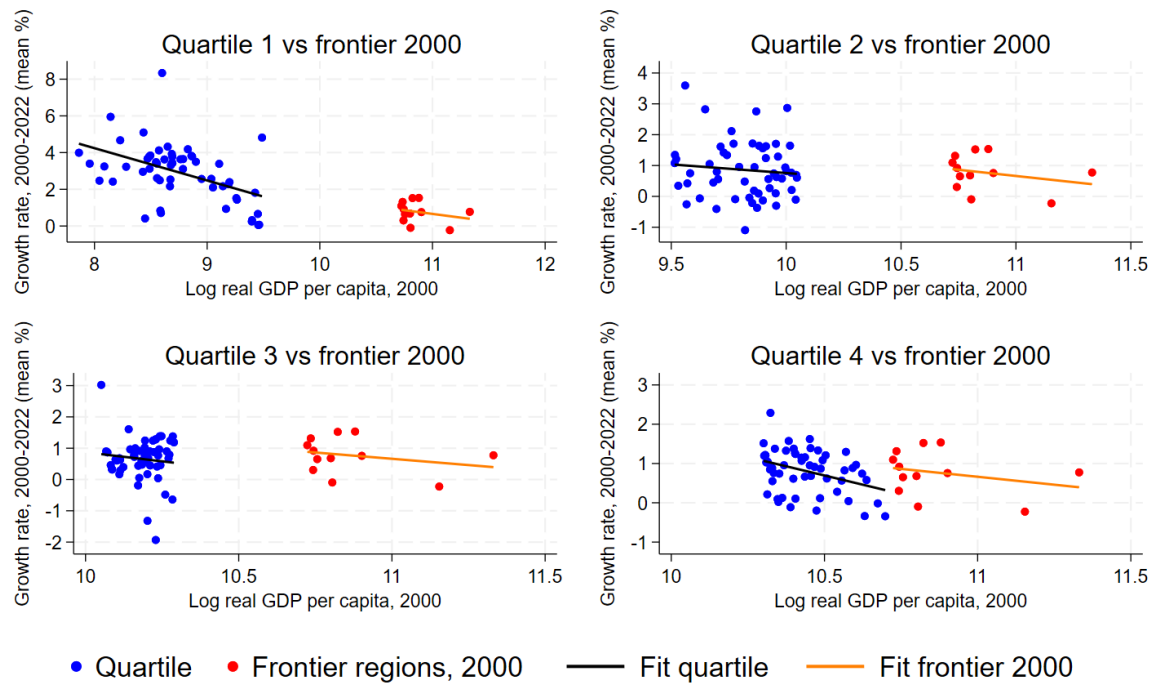


Figure 4: Overall *EU Structural funds* by quartile.

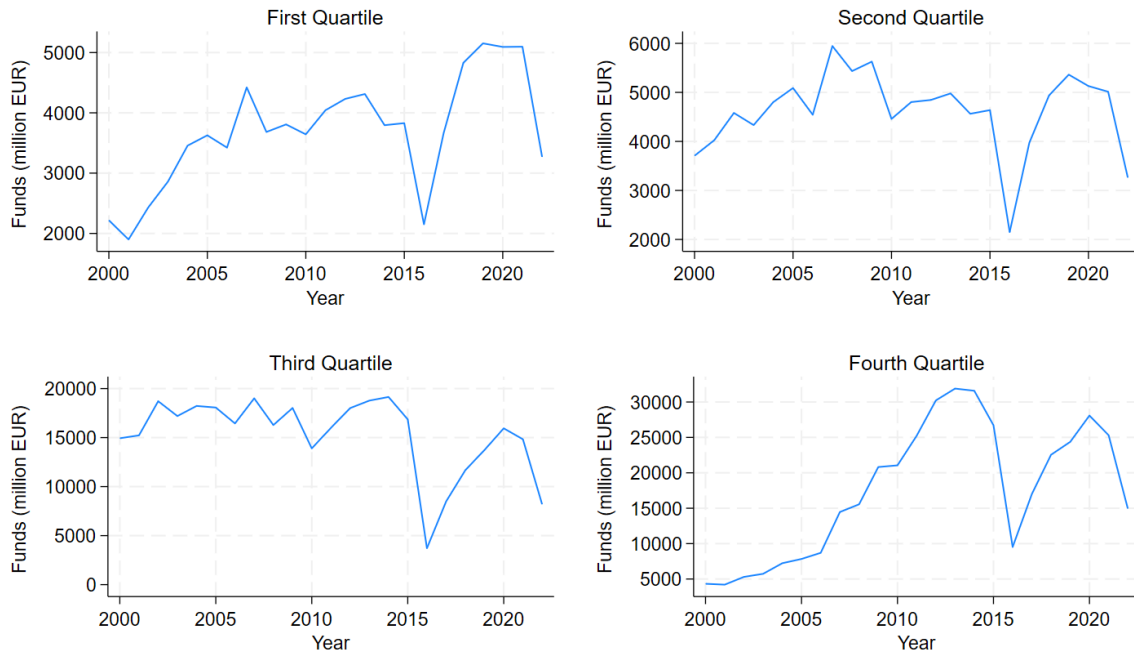


Figure 5: Mean of the *Misallocation* (Eq. 6) by quartile.

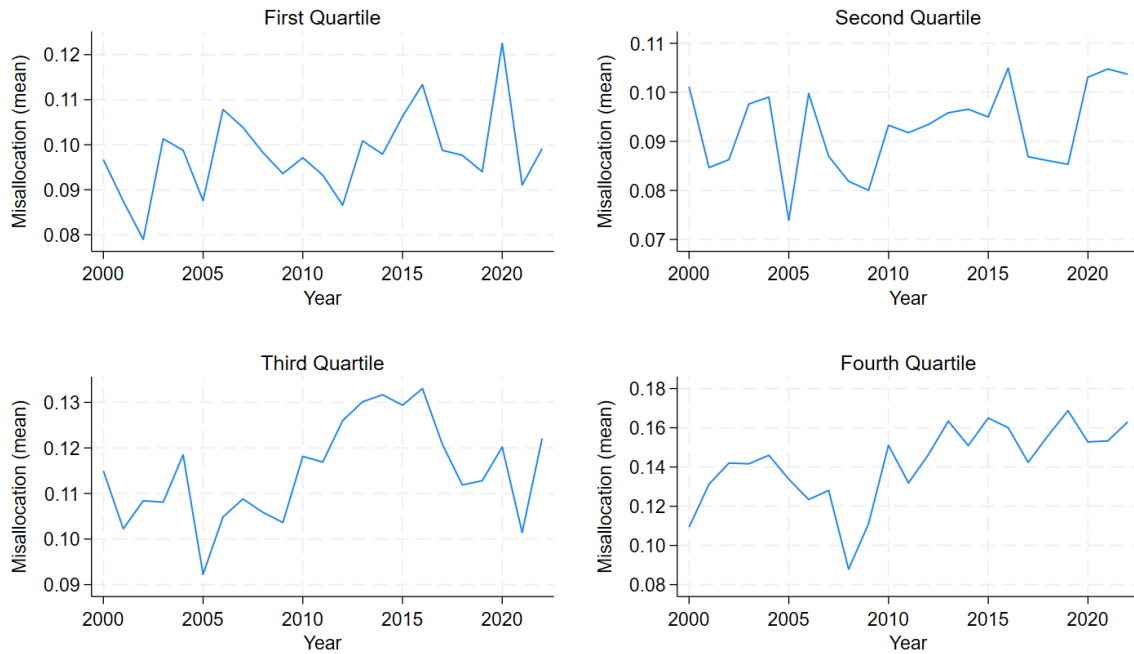


Table 3: EU Funds, Misallocation, and Regional Convergence (3SLS Estimates, eq. 7 and 8).

	(1) 3SLS	(2) Panel FE	(3) Panel FE
<i>Dependent variable:</i>			
<i>Misallocation_{r,t-1}</i>			
EU <i>Funds_{r,t-2}</i>	0.00964*** (0.00131)	0.00913*** (0.00137)	
<i>GDPpc_{r,t-2}</i>	-0.0561*** (0.0114)	-0.0579*** (0.0119)	
Constant	0.671*** (0.118)	0.719*** (0.122)	
<i>Dependent variable:</i>			
<i>GDPpc GAP_{r,t}</i>			
<i>Misallocation_{r,t-1}</i>	4.660*** (1.201)		-0.0138 (0.0922)
EU <i>Funds_{r,t-1}</i>	-0.0518*** (0.0142)		0.0326*** (0.00810)
Constant	10.22*** (0.149)		10.64*** (0.0251)
Observations	5516	5528	5778
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Standard errors in parentheses. All variables are in logs. Column (1) reports Three-Stage Least Squares (3SLS) system estimates using the EU eligibility rule as an instrument for EU funds. Columns (2) and (3) report fixed-effects panel estimates. Region and year fixed effects are included in all specifications.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: EU Funds, Misallocation and Regional Convergence by Macro-Regions (3SLS Estimates, eq. 7 and 8).

	(1) North	(2) South	(3) East
<i>Dependent variable:</i>			
<i>Misallocation_{r,t-1}</i>			
EU <i>Funds_{r,t-2}</i>	0.00986*** (0.00189)	0.0271*** (0.00419)	0.0147*** (0.00544)
<i>GDPpc_{r,t-2}</i>	-0.0544*** (0.00446)	-0.311*** (0.0359)	-0.0434*** (0.00477)
Constant	0.655*** (0.0493)	3.287*** (0.361)	0.571*** (0.0641)
<i>Dependent variable:</i>			
<i>GDPpc GAP_{r,t}</i>			
<i>Misallocation_{r,t-1}</i>	27.70*** (9.117)	1.082*** (0.134)	19.06*** (1.700)
EU <i>Funds_{r,t-1}</i>	-0.532*** (0.179)	-0.0573*** (0.00796)	-0.663*** (0.137)
Constant	7.082*** (1.220)	10.41*** (0.0411)	4.790*** (1.042)
Observations	3212	1308	996
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Standard errors in parentheses. All variable are in logs. The table reports ThreeStage Least Squares (3SLS) estimates of the system using the EU eligibility rule as an instrument for EU funds and it is estimated separately for Northern, Southern and Eastern Europe.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Misallocation and Regional Convergence by Quartile (3SLS Estimates, eq. 7 and 8).

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
<i>Dependent variable:</i>				
<i>Misallocation_{r,t-1}</i>				
EU Funds _{r,t-2}	0.0109*** (0.00326)	0.0168*** (0.00294)	0.0186*** (0.00300)	-0.00284 (0.00339)
GDPpc _{r,t-2}	0.114*** (0.0291)	0.0564*** (0.0116)	-0.158*** (0.0246)	-0.0547** (0.0236)
Constant	-1.035*** (0.314)	-0.442*** (0.124)	1.718*** (0.251)	0.541*** (0.199)
<i>Dependent variable:</i>				
<i>GDPpc GAP_{r,t}</i>				
Misallocation _{r,t-1}	-16.29*** (4.599)	-15.98*** (2.025)	3.518*** (0.875)	3.989*** (0.913)
EU Funds _{r,t-1}	0.274* (0.151)	0.484*** (0.103)	-0.101*** (0.0268)	0.00786 (0.0135)
Constant	13.25*** (1.170)	13.05*** (0.429)	10.12*** (0.152)	10.69*** (0.144)
Observations	1454	1426	1425	1211
Region Fe	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes

Standard errors in parentheses. All variable are in logs. The table reports Three-Stage Least Squares (3SLS) estimates of the system using the EU eligibility rule as an instrument for EU funds and it is estimated separately by quartile.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Direct, indirect, and total effects: overall and by quartile.

Effect	Overall	Q1	Q2	Q3	Q4
Direct	-0.052*** (0.014)	0.274* (0.151)	0.484*** (0.103)	-0.101*** (0.027)	0.008 (0.013)
Indirect	0.045*** (0.010)	-0.178** (0.079)	-0.269*** (0.072)	0.065*** (0.017)	-0.011 (0.015)
Total	-0.007 (0.006)	0.096 (0.076)	0.215*** (0.034)	-0.035*** (0.010)	-0.003 (0.012)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: CF and ERDF Funds, Misallocation and Regional Convergence Overall and by Quartile, eq. 7 and 8).

	(1) Overall	(2) Q1	(3) Q2	(4) Q3	(5) Q4
<i>Dependent variable:</i>					
<i>Misallocation_{r,t-1}</i>					
EU Funds _{r,t-2}	0.00676*** (0.00111)	0.00385* (0.00203)	0.0103*** (0.00204)	0.0110*** (0.00262)	-0.00634* (0.00337)
GDPpc _{r,t-2}	-0.0532*** (0.0109)	0.117*** (0.0290)	0.125*** (0.00876)	-0.119*** (0.0284)	-0.0709*** (0.0236)
Constant	0.631*** (0.112)	-1.098*** (0.311)	-1.162*** (0.0929)	1.307*** (0.289)	0.659*** (0.199)
<i>Dependent variable:</i>					
<i>GDPpc GAP_{r,t}</i>					
Misallocation _{r,t-1}	4.225*** (1.475)	-15.51*** (4.053)	-6.257*** (0.580)	4.698*** (1.076)	3.497*** (0.952)
EU Funds _{r,t-1}	-0.0371*** (0.0126)	0.0485 (0.0637)	0.123*** (0.0277)	-0.0841*** (0.0234)	0.0313** (0.0140)
Constant	10.27*** (0.166)	12.27*** (0.788)	11.54*** (0.157)	10.02*** (0.168)	10.82*** (0.149)
Observations	5477	1430	1414	1422	1211
Region Fe	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. All variable are in logs. The table reports Three-Stage Least Squares (3SLS) estimates of the system using the EU eligibility rule as an instrument for CF and ERDF funds and it is estimated overall and separately by quartile.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Direct, indirect, and total effects using CF and ERCF funds: overall and by quartile.

Effect	Overall	Q1	Q2	Q3	Q4
Direct	-0.037*** (0.013)	0.048 (0.064)	0.123*** (0.028)	-0.084*** (0.023)	0.031** (0.014)
Indirect	0.029*** (0.009)	-0.060* (0.036)	-0.064*** (0.015)	0.052*** (0.015)	-0.022 (0.016)
Total	-0.009 (0.006)	-0.011 (0.031)	0.058*** (0.013)	-0.032*** (0.009)	0.009 (0.015)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Firm-level capital misallocation as a brake on innovation

A joint work with Massimo Del Gatto

Abstract

This paper studies how capital misallocation shapes firm-level technology adoption and how innovation subsidies interact with these distortions. We develop a model of heterogeneous firms in which idiosyncratic capital wedges affect production and technology choices. The model predicts that distortions reduce adoption and that subsidies become less effective as capital wedges intensify. At the aggregate level, a positive correlation between distortions and productivity weakens selection and lowers total technology. Using firm-level data, we find evidence consistent with these mechanisms. Distortions significantly depress the average technology adoption, and eliminating the systematic distortion generates counterfactual sectoral technology gains of around 15 percent with a marked impact in high tech and capital-intensive industries. The results imply that innovation policy effectiveness depends critically on the efficiency of capital allocation.

Keywords: Capital Misallocation; Technology Adoption; Innovation Policy; Productivity; Heterogeneous Firms

JEL Classification: D24; O33; O47; E22

1 Introduction

Technology adoption is a key margin through which firms improve productivity, yet it is costly and uneven across producers. Adopting advanced production technologies typically requires substantial investment and access to capital, implying that financial conditions play an important role in shaping firms' adoption decisions. Government intervention in innovation is often motivated by knowledge spillovers and financing frictions, which can lead firms to underinvest in technologically advanced activities [Howell \(2024\)](#). At the same time, a growing body of evidence shows that the effectiveness of innovation policies is highly heterogeneous across firms and depends on firm-specific characteristics. In particular, the impact of public support on firms' innovation investment may vary with the underlying economic environment and with the degree to which firms can appropriate returns from innovation [Gelabert et al. \(2009\)](#). In parallel, a large literature documents that cross-firm inefficiencies can generate sizeable aggregate productivity losses [Restuccia and Rogerson \(2008\)](#); [Hsieh and Klenow \(2009\)](#). When distortions affect firms asymmetrically, more productive firms may operate below efficient scale while less productive firms absorb resources, weakening the link between productivity and firm size and reducing aggregate efficiency.

An important implication is that distortions are often systematically related to firm productivity. Empirical and quantitative evidence indicates that more productive firms may face relatively higher wedges, due to financial frictions, regulatory constraints, or other distortions [Bento and Restuccia \(2017\)](#). These patterns are particularly consequential because they not only reduce static allocative efficiency but may also affect firms' investment incentives. If the returns to expanding scale or upgrading technology cannot

be fully realised due to distortions, firms may reduce or postpone technology adoption. Misallocation therefore affects not only the level of productivity at a given point in time, but also the mechanisms through which productivity evolves.

While the consequences of misallocation are well documented, its interaction with firms' technology adoption decisions and with innovation policies remains less understood. A related literature studies how financial frictions influence firm investment and capital accumulation in heterogeneous-firm environments [Midrigan and Xu \(2014\)](#); [Ottonello and Winberry \(2023\)](#), and recent work shows that distortions correlated with productivity can affect firms' incentives to innovate and upgrade technologies, with important aggregate implications [Pinzon \(2025\)](#). However, empirical evidence on how capital misallocation interacts with technology adoption subsidies remains limited. This interaction is relevant because innovation policies typically operate through financial incentives whose impact may depend on the underlying allocation of capital across firms. Consistently, survey evidence shows that the effectiveness of innovation policies is highly heterogeneous and tends to be stronger for financially constrained and younger firms, highlighting the importance of firm-level conditions for policy transmission [Howell \(2024\)](#). This suggests that the impact of innovation policies depends not only on access to finance, but also on how resources are allocated across firms [Acemoglu et al. \(2018\)](#).

This paper studies how capital market distortions influence firms' technology adoption decisions and the empirical effectiveness of innovation subsidies. The central hypothesis is that wedges affecting the cost of capital reduce adoption incentives and attenuate the association between subsidies and adoption, particularly when distortions are systematically related to firm productivity. The focus on capital misallocation is motivated by the capital-intensive nature of adoption investments and by the fact that capital wedges provide a natural channel linking financial frictions to heterogeneous adoption outcomes.

The paper makes three contributions. First, it develops a tractable model that integrates heterogeneous-firm competition, endogenous technology adoption, and firm-specific capital wedges. Building on the quality-competition framework of [Antoniades \(2015\)](#), technology adoption is modelled as a quality-enhancing investment, while capital distortions follow the wedge-based logic of [Hsieh and Klenow \(2009\)](#). This structure delivers clear predictions on how distortions affect both the extensive and intensive margins of adoption and on how subsidies interact with wedges. Second, the paper provides new empirical evidence using firm-level data from INAPP that jointly observe technology adoption, related innovation subsidies, and balance sheet information, allowing a direct analysis of adoption outcomes in the presence of capital frictions. Third, it quantifies aggregate implications by linking micro estimates to an equilibrium mapping for sectoral technology and conducting counterfactual exercises that shut down the systematic component of misallocation.

The mechanism is straightforward. Firms differ in productivity and face idiosyncratic wedges in the cost of capital. Technology adoption increases efficiency but requires investment; higher wedges raise the effective cost of adoption and reduce optimal adoption choices. Subsidies lower adoption costs and are associated with higher adoption on average, but their association with adoption weakens when wedges are large, as financially constrained firms may be less able to translate policy support into technology investment [Howell \(2024\)](#). The model therefore predicts heterogeneous adoption responses across firms depending on the degree and direction of capital distortions.

To test these predictions, the empirical analysis combines two complementary data sources for Italy. The INAPP survey provides detailed firm-level information on the

adoption of advanced production technologies—including digital and high-tech capital investments such as robotics, automation systems, cloud computing, and other Industry 4.0 applications—together with related expenditures and receipt of public innovation subsidies. Unlike standard datasets focused on R&D activity, these data capture the implementation of frontier production technologies directly at the firm level. The AIDA database supplies balance sheet information used to compute productivity and capital wedges in the spirit of [Hsieh and Klenow \(2009\)](#). Merging the two sources yields a firm-level sample in which technology adoption, policy support, and capital frictions are jointly observed. The empirical strategy estimates selection models (Hurdle and Heckman) of adoption on capital distortions, subsidies, and their interaction, distinguishing between the decision to adopt and the intensity of adoption conditional on adoption.

The results are consistent with the model’s mechanisms. Firms facing higher capital distortions are less likely to adopt advanced technologies, with distortions primarily associated with the extensive margin. Innovation subsidies are positively associated with adoption on average, but the interaction between subsidies and distortions is negative, indicating that the association between subsidies and adoption weakens in more distorted environments. This pattern is consistent with evidence showing that the impact of innovation policies depends on firm-level constraints and targeting, and may be limited when firms are unable to convert financial support into innovative investment [Howell \(2024\)](#). It also aligns with frameworks emphasising that policy effectiveness cannot be evaluated independently of the allocative environment in which firms operate [Acemoglu et al. \(2018\)](#). The analysis builds on the misallocation framework of [Hsieh and Klenow \(2009\)](#) and on subsequent work highlighting the role of the correlation between productivity and distortions for aggregate outcomes [Bento and Restuccia \(2017\)](#), and complements recent research on the link between distortions and innovation [Pinzon \(2025\)](#). At the aggregate level, sectoral estimates of productivity dispersion, distortion–productivity correlations, and cutoff parameters are combined with the model’s equilibrium mapping to quantify counterfactual changes in sectoral technology when the systematic component of misallocation is removed. The implied gains are largest in manufacturing and construction.

The remainder of the paper is organised as follows. Section 2 presents the theoretical model. Section 3 describes the data. Section 4 outlines the firm-level empirical strategy and reports the results. Section 5 discusses aggregate implications. Section 6 concludes.

2 Model

To understand how market distortions affect firms’ decisions on technology adoption and overall productivity, we develop a model that captures key features of firm heterogeneity and input market imperfections. This framework builds on Antoniadou (2015), who models firm-level quality choice assuming that marginal costs increase linearly with product quality. We retain a similar marginal cost structure, combining a base production term with a quality-related component, but reinterpret these elements to incorporate two critical dimensions relevant to technology adoption.

First, we redefine the endogenous firm decision variable from product quality to the adoption of advanced production technologies, such as automation, digital integration, or AI systems. These technologies influence both marginal and total costs while enhancing the perceived and functional attributes of the product—including precision, durability, compatibility, and compliance with technical standards. As a result, technology adoption

enters consumer preferences as a vertical quality attribute, effectively mapping one-to-one with quality in the demand framework.¹ This reinterpretation aligns with insights from Flam and Helpman (1987) and Fajgelbaum et al. (2011) about differentiation and quality. Together, these allow us to leverage the demand structure of Antoniades (2015) while shifting the focus to technology investment decisions, incorporating firm-level distortions and subsidies.

Second, we introduce a misallocation mechanism through a firm-specific distortion on the cost of capital, which serves as a proxy for capital-constrained firms. This distortion reflects deviations from competitive input pricing due to wedges, such as financial frictions or policy inefficiencies. Firms facing higher distortions encounter elevated input costs, leading to altered behavior in technology adoption. Modeling distortions as wedges affecting firms' input costs is consistent with evidence that policy-induced frictions can act as implicit taxes on firm growth and innovation Aghion et al. (2023).

Third, we incorporate policy interventions via subsidies on the fixed costs of technology adoption. These subsidies reduce the effective cost of investing in new technologies and, in interaction with capital distortions, enable analysis of differential policy impacts across firms. This formulation reflects the idea that public support can relax financing constraints and stimulate innovation, but its impact may vary substantially across firms depending on their underlying conditions Howell (2017) Howell (2024).

The model is set in a static framework with a representative consumer and a continuum of heterogeneous firms producing differentiated varieties. Firms differ in productivity and face idiosyncratic distortions and subsidies. Based on their productivity, distortions, and subsidies, firms decide on optimal technology adoption, production levels, and market participation. We focus on the steady-state equilibrium to derive firm-level decisions and aggregate outcomes.

We formalize the demand side following Antoniades (2015), which builds on the Melitz and Ottaviano (2008) model of linear demand preferences and endogenous markups. In our framework, the demand incorporates consumers' preferences for technology adoption, which enters as a vertical attribute analogous to quality. The utility function is augmented to include the technological level of each variety.

From Antoniades (2015), the representative consumer's utility is given by:

$$U = q_0 + \alpha \int_{i \in \Omega} q_i di + \rho \int_{i \in \Omega} z_i q_i di - \frac{\gamma}{2} \int_{i \in \Omega} (q_i)^2 di - \frac{1}{2\eta} \left(\int_{i \in \Omega} q_i di \right)^2, \quad (1)$$

where q_0 and q_i represent the individual's consumption of the numeraire good and each variety i , respectively. The technological level of each variety is given by z_i .

The parameters α and η capture the degree of substitution between each variety and the numeraire, while γ captures the degree of differentiation among the varieties. Finally, ρ is a taste parameter for technology that can vary across countries and industries. All parameters are assumed to be positive.

If $z_i \equiv 0$ for all firms, the utility function reduces to that of Melitz and Ottaviano (2008). The inverse demand for each variety is given by: $p_i = \alpha - \gamma q_i + \rho z_i - \eta Q^c$, where $Q^c = \int_{i \in \Omega} q_i di$. By inverting this, we obtain the demand for each variety consumed:

¹Although technology adoption could in principle be modelled as a direct shifter of firm-specific total factor productivity, we retain the vertical quality formulation following Antoniades (2015). This approach preserves consumers' direct valuation of technological sophistication in their utility while maintaining an explicit trade-off between the benefits of higher quality and the associated increase in marginal production costs. The two interpretations are not isomorphic once both demand and cost channels are considered.

$$q_i = Lq_i^c = \frac{\alpha L}{\eta N + \gamma} - \frac{L}{\gamma} p_i + \frac{L\rho}{\gamma} z_i + \frac{\eta N L}{\eta N + \gamma} \bar{p} - \frac{\eta N L \rho}{\eta N + \gamma} \bar{z}. \quad (2)$$

where N is the number of varieties consumed, L is the size of the country, $\bar{p} = (1/N) \int_{j \in \Omega^c} p_j dj$, $\bar{z} = (1/N) \int_{j \in \Omega^c} z_j dj$, and $\Omega^c \subset \Omega$ is the subset of varieties consumed. This preference structure ensures that the demand for good i is linear in price and technology.

On the supply side, firms produce differentiated varieties using labor and capital as inputs, under a Cobb-Douglas production technology with constant returns to scale. Firm productivity is denoted as the inverse ψ_i following Melitz (2003), where lower ψ_i indicates higher productivity. Additionally, firms face idiosyncratic distortions in the capital market, captured by a wedge τ_i , which acts as an implicit tax on the cost of capital.

Following Corcos et al. (2012), the base unit cost c_i reflects input prices, productivity, and distortions, incorporating factor shares and extended to include capital distortions. Specifically,

$$c_i = \omega \psi_i t_i, \quad \omega = \left(\frac{R}{\beta_K} \right)^{\beta_K} \left(\frac{W}{\beta_L} \right)^{\beta_L}, \quad t_i = (1 + \tau_i)^{\beta_K}. \quad (3)$$

Here, ω is the undistorted price index of the composite input, with R and W denoting the rental rate of capital and the wage rate, respectively, and β_K and β_L (with $\beta_K + \beta_L = 1$) representing the capital and labor shares. The term $t_i > 0$ captures the distortionary wedge, where $t_i = 1$ (equivalently, $\tau_i = 0$) implies economic efficiency with no distortion.

²

- For $\tau_i > -1$, a positive τ_i increases the effective cost of capital (implicit tax). Firms with $t_i > 1$ (positive τ_i) are **inefficiently small**, as they face higher effective capital costs and operate below their efficient scale; accordingly, $t_i > 1$ identifies firms that are capital constrained.
- For $-1 < \tau_i < 0$, a negative τ_i reduces the effective cost of capital. Firms with $t_i < 1$ (negative τ_i) are **inefficiently large**, as they benefit from a lower implicit tax on capital that results in over-utilization of capital relative to their productivity.

This formulation implies that the absolute value of τ_i proportionally distorts the cost of capital relative to the efficient benchmark.

The marginal cost of production for firm i , m_i , consists of this base unit cost c_i and an additional term associated with technology adoption σz_i , where $\sigma > 0$ represents the unit cost of incorporating technology z_i into production:

$$m_i = c_i + \sigma z_i. \quad (4)$$

²Because the production technology is Cobb-Douglas with constant returns to scale, the capital wedge t_i scales the entire composite input cost c_i . Consequently, it is formally equivalent to a proportional distortion on output or labor productivity. While we interpret t_i as a capital-specific wedge (consistent with the focus on capital misallocation), the reader should note that the model does not isolate a purely capital-specific channel; any factor-specific distortion would enter the unit cost in an isomorphic way under Cobb-Douglas technology.

Empirical evidence as [Juhász et al. \(2024\)³](#) supports this separation of innovation-related costs from standard production expenses, as technology adoption often involves organizational challenges and complementarities that are distinct from variable production costs. This structure allows us to examine how capital misallocation affects technology adoption through its impact on marginal costs.

To incorporate policy interventions, we model the total cost function for firm i is thus:

$$TC_i = q_i(c_i + \sigma z_i) + \theta(1 - s_i)z_i^2, \quad (5)$$

where the first term represents variable costs, and the second captures a convex adjustment cost that is quadratic in the technological level z_i . This formulation captures the increasing marginal cost of raising the firm's technological sophistication (organizational restructuring, training, integration of new systems, etc.) while remaining separable from variable production costs. Here, $s_i \in [0, 1]$ is the firm-specific subsidy rate that reduces the quadratic adjustment cost of technology adoption, $\theta(1 - s_i)z_i^2$. This cost component is independent of the quantity produced q_i and depends only on the chosen technological level z_i . The parameter $\theta > 0$ governs the sector-level cost of upgrading technology and innovation. Modelling the subsidy on this term allows the policy intervention to target firms' technology adoption decision separately from variable production costs. Higher subsidies incentivize greater technology adoption. At the same time, recent evidence highlights that the impact of subsidies depends on firms' ability to translate financial support into innovation, which may be limited in the presence of other constraints [Howell \(2024\)](#). Ceteris paribus, more productive firms (lower ψ_i) and those with lower capital distortions (lower τ_i) face reduced base costs c_i , enabling higher investment in z_i .

In equilibrium, the quantity produced satisfies

$$q_i = \frac{L}{\gamma}(p_i - c_i - \sigma z_i). \quad (6)$$

Using the demand function from equation (2), we derive the price, quantity, and profit equations as functions of the marginal cost cutoff c_d , c_i , and z_i :

$$p(c_i, z_i) = \frac{1}{2}[(c_d + c_i) + (\rho + \sigma)z_i], \quad (7)$$

$$q(c_i, z_i) = \frac{L}{2\gamma}[(c_d - c_i) + (\rho - \sigma)z_i], \quad (8)$$

$$\pi(c_i, z_i) = \frac{L}{4\gamma}[(c_d - c_i) + (\rho - \sigma)z_i]^2 - \theta(1 - s_i)z_i^2. \quad (9)$$

³Empirical evidence from the industrialization process in France suggests that technology adoption requires significant organizational restructuring beyond standard production costs (Technology Adoption and Productivity Growth). As highlighted, "initial information disparities about the optimal organization of production can help to explain why breakthrough technologies tend to be adopted slowly," indicating that innovation costs are not simply a function of production efficiency. Moreover, the adoption of new technologies involves "organizational challenges, such as optimal plant layout, and they exhibit complementarities in the production function." This supports the modeling choice of separating the standard variable cost component $\omega\psi_it_i$ from the technological adoption cost σz_i , as firms must allocate resources to both production and adaptation processes independently.

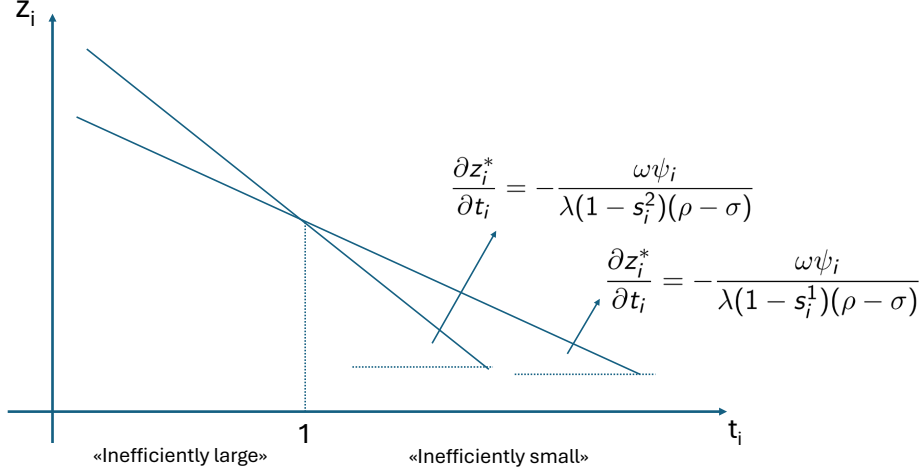


Figure 1: The figure represents the relationship between distortion and technological adoption.

Firm-level optimal technological choice

Since the distortion τ_i enters incrementally through m_i , an increase in τ_i raises marginal costs, leading to higher equilibrium prices relative to the efficient benchmark, while a decrease in τ_i has the opposite effect.

Firms then choose the optimal technology level z_i^* by maximizing profits in equation (9), yielding:

$$z_i^* = \frac{c_d - \omega\psi_i t_i}{\lambda(1 - s_i) - (\rho - \sigma)}, \quad (10)$$

where $\lambda = \frac{4\theta\gamma}{L(\rho-\sigma)}$. To ensure $z_i^* > 0$, we assume $\lambda(1 - s_i) > (\rho - \sigma)$.⁴

Given the previous assumptions on the parameters and the form of z_i^* , to observe the effect of misallocation τ_i on the firm's technology adoption z_i^* , we derive the partial derivative of equation (10) with respect to t_i , obtaining:

$$\frac{\partial z_i^*}{\partial t_i} = -\frac{\omega \cdot \psi_i}{\lambda \cdot (1 - s_i) - (\rho - \sigma)} < 0. \quad (11)$$

This result highlights the direct impact of firm-level distortion τ_i on the optimal technology adoption z_i^* . Specifically, an increase in τ_i reduces z_i^* , reflecting the negative effect of capital distortions on technological adoption. Conversely, a reduction in τ_i increases optimal technology adoption. The same logic applies to subsidies: the partial derivative of z_i^* with respect to s_i is positive, so that higher subsidies are associated with greater technology adoption.

Figure 1 illustrates the relationship between the distortion wedge t_i and the optimal technology adoption z_i^* for two different levels of subsidies, s^1 and s^2 (where $s^1 < s^2$). The horizontal axis represents t_i , with the value of 1 denoting the benchmark of no distortion ($\tau_i = 0$). Values of $t_i > 1$ (positive τ_i) correspond to firms facing a higher effective cost

⁴We impose $\rho > \sigma$ and $\lambda(1 - s_i) > (\rho - \sigma)$ to guarantee an interior solution with $z_i^* > 0$. Economically, $\rho > \sigma$ requires that consumers' valuation of technological sophistication exceeds its marginal production cost, generating a positive incentive for adoption. The stricter condition $\lambda(1 - s_i) > (\rho - \sigma)$ further ensures that the (subsidized) convex adjustment cost of adoption is not prohibitively high relative to the net marginal benefit of technology in equilibrium.

of capital (more constrained), while values of $t_i < 1$ (negative τ_i) correspond to firms facing a lower effective cost of capital. The two downward-sloping lines depict the partial derivative $\partial z_i^* / \partial t_i$ for each subsidy level, highlighting the negative impact of distortions on technology adoption. The steeper slope for the higher subsidy level (s^2) demonstrates that subsidies amplify the adverse effect of capital distortions: as t_i increases, capital-constrained firms experience a more pronounced reduction in z_i^* . This underscores the model's key insight that, in the presence of capital misallocation, subsidies may exacerbate inefficiencies by disproportionately hindering technology investment among more constrained firms.

Testable Implication 1: Equation (11) implies that firms facing higher capital distortions exhibit lower optimal technology adoption. Holding other factors constant, a higher τ_i (indicative of tighter capital constraints) is associated with a reduced level of advanced production technology investment.

Moreover, in order to observe the combined effect of misallocation and subsidies on the firm's technology adoption, we compute the derivative of equation (11) with respect to subsidies s_i .

We then obtain:

$$\frac{\partial^2 z_i^*}{\partial t_i \partial s_i} = -\frac{\lambda \omega \cdot \psi_i}{[\lambda(1 - s_i) - (\rho - \sigma)]^2} < 0 \quad (12)$$

This cross-partial derivative shows how changes in s_i shape the influence of τ_i on z_i^* . Because it is negative, an increase in s_i amplifies the negative slope $\frac{\partial z_i^*}{\partial \tau_i}$. In other words, the stronger the subsidy, the more adverse the impact of misallocation becomes. Hence, rather than cushioning technology adoption from misallocation, s_i exacerbates its harmful effects. Overall, the model implies that subsidies deepen the distortionary consequences of misallocation on z_i^* .

Testable Implication 2: Equation (12) implies that subsidies intensify the distortion channel. Holding other factors constant, the marginal effect of tighter capital constraints τ_i on optimal technology adoption z_i^* becomes more negative as the level of subsidies s_i increases.

Aggregate technology

To derive the aggregate implications of the model, we need to specify how firm-level distortions are related to productivity. Following Bento and Restuccia (2017) and Pinzon (2025), we assume that distortions are systematically correlated with firm productivity. We thus decompose the distortion wedge as

$$t_i = \psi_i^{-\chi} e_i, \quad (13)$$

where $\chi \in [0, 1]$ governs the elasticity of distortions with respect to productivity and e_i is an idiosyncratic component with mean one. Substituting into the base unit cost yields

$$c_i = \omega \psi_i t_i = \omega \psi_i^{1-\chi} e_i.$$

When we focus on the deterministic (systematic) component of misallocation, we set $e_i = 1$, which simplifies to $t_i = \psi_i^{-\chi}$ and $c_i = \omega \psi_i^{1-\chi}$. When $\chi = 0$, distortions are

unrelated to productivity. When $\chi > 0$, more productive firms (lower ψ_i) face relatively higher wedges, weakening selection and reducing aggregate efficiency. This reduced-form relationship provides a tractable mapping from micro distortions to aggregate outcomes and allows us to derive closed-form expressions for the productivity cutoff and sectoral technology.

To understand this relationship, consider the process step by step. Firm-level total factor productivity represents the efficiency with which a firm combines inputs to produce output. In environments with misallocation—common in economies like Italy—distortions such as capital constraints, regulatory barriers, or uneven access to finance are not randomly assigned but are systematically linked to this underlying productivity. The parameter χ acts as an elasticity that determines how sensitive distortions are to productivity levels. When $\chi = 0$, there is no systematic correlation. However, when $0 < \chi < 1$, a systematic positive correlation emerges: firms with higher productivity (lower ψ_i) face disproportionately higher distortions (higher t_i), reflecting empirical patterns where efficient firms are penalized more severely — due to frictions such as size-dependent regulations, corruption targeting growing firms, or financial frictions that limit expansion of high-potential entities. The parameter χ determines how strongly distortions are systematically related to productivity and therefore how misallocation affects equilibrium selection and aggregate outcomes. To maintain analytical tractability, we assume that subsidies s are uniform across firms, representing a sector-level policy intervention. We assume that productivity draws ψ_i follow a Pareto distribution:

$$G(\psi) = \left(\frac{\psi}{\psi_m} \right)^{k(1-\chi)}, \quad \text{for } \psi \in [0, \psi_m],$$

with shape parameter k and upper bound $c_M = \omega \psi_m^{1-\chi}$, with $k \geq 1$ and $0 \leq \chi < 1$ (ensuring $1 - \chi > 0$ for a positive exponent and preserving the Pareto form).⁵ Firms enter the market expecting zero expected profits. Let $f_E > 0$ denote the (sunk) entry cost. This gives rise to the free-entry condition:

$$f_E = \int_0^{c_d} \left[\frac{L}{4\gamma} ((c_d - c_i) + (\rho - \sigma)z_i)^2 - \theta(1 - s)z_i^2 \right] dG(c). \quad (14)$$

Substituting the expression for $z_i^* = \frac{\omega(\psi_d^{1-\chi} - \psi_i^{1-\chi})}{\lambda(1-s) - (\rho - \sigma)}$ from equation (10) and solving the integral under the Pareto assumption with shape $k(1 - \chi)$, we obtain a closed-form expression for the productivity cutoff:

$$\psi_d = \left(f_E \cdot \frac{[\lambda(1 - s) - (\rho - \sigma)]^2 (k + 1)(k + 2) \psi_m^{k(1-\chi)}}{2(1 - s) \left[\frac{L}{4\gamma} \lambda^2 (1 - s) - \theta \right] \omega^2} \right)^{\frac{1}{(k+2)(1-\chi)}}. \quad (15)$$

The elasticity of the cutoff with respect to ψ_m is $\partial \ln \psi_d / \partial \ln \psi_m = k/(k + 2) < 1$, so the response of selection to shifts in the productivity support is dampened when k is larger. The correlation parameter χ affects ψ_d through the equilibrium exponent $1/((k + 2)(1 - \chi))$, thereby changing the sensitivity of selection to the other fundamentals entering the free-entry condition. When $\chi > 0$, correlated distortions impose higher

⁵We require $k \geq 1$ to ensure finite moments of the productivity distribution and $0 \leq \chi < 1$ to guarantee that the exponent $1 - \chi > 0$, thereby preserving the Pareto shape of the cost distribution after the systematic distortion $t_i = \psi_i^{-\chi}$.

wedges on more productive firms (lower ψ_i) via $t_i = \psi_i^{-\chi}$, diminishing their competitive edge and easing market survival for less productive firms, which in turn hampers aggregate efficiency and reduces technology adoption at the sectoral level.

To compute average technology adoption, we integrate the optimal firm-level decision z_i^* over the support of surviving firms, i.e., $\bar{z} = \frac{1}{G(\psi_d)} \int_0^{\psi_d} z_i^* dG(\psi)$, which, under the Pareto assumption with shape $k(1 - \chi)$, yields a closed-form expression for average technology adoption:

$$\bar{z} = \frac{\omega \psi_d^{1-\chi}}{(k+1)[\lambda(1-s) - (\rho - \sigma)]}. \quad (16)$$

Holding the cutoff ψ_d fixed, the partial derivative of average technology adoption with respect to χ is $\frac{\partial \bar{z}}{\partial \chi} \Big|_{\psi_d} = -\bar{z} \ln \psi_d$, which is negative whenever $\psi_d > 1$.⁶

This equation highlights the theoretical link between systematic misallocation and aggregate technology. In our model, average technology adoption is proportional to $\psi_d^{1-\chi}$, so that, holding the cutoff fixed, a higher value of χ reduces $\bar{z}$ whenever $\psi_d > 1$. Intuitively, a stronger correlation between distortions and productivity (higher χ) penalizes more productive firms, diminishing their incentives to adopt technology and thereby lowering average adoption across the sector.

Within the model specification, since average technology adoption depends multiplicatively on the productivity cutoff and on a set of sector-specific scaling parameters, the comparison between the distorted equilibrium and the efficient benchmark can be considerably simplified. In particular, all common terms — including the cost shifter ω and the denominator $(k+1)[\lambda(1-s) - (\rho - \sigma)]$ — cancel out when computing relative differences. As a result, potential gains from eliminating misallocation depend exclusively on the change in the effective productivity term induced by the distortion parameter χ . We can thus conduct the counterfactual normalizing and express technology gains in reduced form, isolating the role of misallocation independently from sectoral cost parameters and subsidy levels. Intuitively, removing distortions is equivalent to moving from an economy where firm productivity enters with exponent $(1 - \chi)$ to one where it enters linearly, generating proportional improvements that increase with both the degree of misallocation and the productivity cutoff. This yields $\psi_d^{ctf} \equiv \psi_d$ since χ is 0.

$$Z^{gains} \equiv \frac{\psi_d^{ctf} - \psi_d^{1-\chi}}{\psi_d^{1-\chi}} \equiv \frac{\psi_d - \psi_d^{1-\chi}}{\psi_d^{1-\chi}} \quad (17)$$

3 Data

Our empirical analysis combines firm-level survey information from the RIL survey, conducted by INAPP (National Institute for Public Policy Analysis), with balance-sheet data from AIDA (Bureau van Dijk). The RIL survey covers more than 30,000 firms and is representative of the Italian economy. It provides detailed information on firm characteristics, innovation activities, and public support received over the period 2019–2021.

The survey includes standard firm demographics (legal form, location, year of establishment, sector classification according to ATECO 2007), ownership and governance

⁶This derivative is negative whenever $\psi_d > 1$, a condition that always holds in equilibrium. It requires that the productivity cutoff lies strictly above the normalized efficient benchmark ($\psi = 1$), ensuring active selection of firms into the market. This captures the direct effect of a stronger distortion–productivity correlation on average technology adoption for a given selection threshold.

characteristics, and workforce composition. These variables allow us to control for observable heterogeneity in firm structure and managerial organization.

Technology adoption is measured using firms' reported expenditure in 2021 on digital and advanced production technologies, including IoT, robotics, cloud computing, artificial intelligence, cybersecurity, 3D printing, and related applications. This measure captures realized capital expenditures associated with technological upgrading rather than R&D inputs. Figure 3 reports the sectoral distribution of technology adoption. The distribution is highly skewed, with a large mass at zero across all sectors, indicating that a substantial fraction of firms do not undertake technology investment. Information on public support is drawn from detailed survey responses on technology-specific incentives received in 2020–2021. These include the *Credito d'imposta* for capital goods and innovation, *Nuova Sabatini*, *Patent Box*, and the *Credito d'imposta Mezzogiorno*. The distribution of subsidies is shown in Figure 4. As with adoption, a substantial mass of firms receives no support, with broadly similar distributional patterns across sectors.

We merge the survey with AIDA balance-sheet data to construct measures of productivity, capital intensity, and financial performance. Capital misallocation is proxied by the deviation of firm-level marginal revenue product of capital from its two-digit sectoral mean. Figure 2 shows that measured misallocation is present across all sectors.

Table 5 summarizes baseline firm-level relationships between capital misallocation, subsidies, and technology adoption. In addition, Figure 8 documents the main bivariate associations: technology adoption is negatively correlated with capital misallocation and positively correlated with innovation subsidies. These patterns motivate the econometric specifications that follow.

The final dataset provides joint information on technology adoption, public support, capital misallocation, and firm productivity, allowing us to examine both firm-level adoption decisions and their aggregate implications.

4 Analysis

We first estimate firm-level total factor productivity and capital misallocation following the approach of Calligaris et al. (2016). For each two-digit sector s , we estimate a sector-specific Cobb-Douglas production function

$$Y_{it} = A_{it} K_{it}^{\alpha_s} L_{it}^{\beta_s}, \quad (18)$$

where Y is value added, K is the capital stock, L is employment, and A_{it} denotes firm-level total factor productivity. The sector-specific output elasticities α_s and β_s are estimated by OLS. Firm-level TFP A_i is then recovered as the residual from this estimation. Using the estimated capital share α_s , we compute the marginal revenue product of capital as $MRPK_i = \alpha_s \times \frac{Y_{it}}{K_{it}}$. The firm-specific capital distortion τ_i (our measure of misallocation) is then defined as the log deviation of firm i 's MRPK from the sector-year mean:

$$\tau_i = \ln(MRPK_i) - \overline{\ln(MRPK)}_{s,t}. \quad (19)$$

Positive values of τ_i indicate capital-constrained (inefficiently small) firms, while negative values indicate firms that are inefficiently large. A potential concern is that input choices may be correlated with unobserved productivity shocks, which could bias the estimated output elasticities α_s and β_s . Following the standard approach in the misallocation literature, we estimate the production function separately at the relatively detailed two-digit

sectoral level and rely on within-sector-year variation to construct our measure of capital misallocation τ_i . This strategy substantially mitigates the impact of any systematic bias on our key variable of interest.

This expression provides the reduced-form empirical analogue of the firm-level wedge introduced in the theoretical model. Positive or negative values of τ_i capture, respectively, under- and over-utilization of capital relative to the efficient allocation and should be interpreted as a reduced-form proxy for capital distortions rather than a structural estimate of the wedge in the model. Consistent with the definitions introduced in the model, firms with $\text{MRPK}_{is} < \text{MRPK}_s$ are classified as *inefficiently large*: they employ more capital than implied by their productivity level, generating marginal returns below the efficient benchmark and reflecting relative capital abundance. Conversely, firms with $\text{MRPK}_{is} > \text{MRPK}_s$ are classified as *inefficiently small*: they operate with insufficient capital, exhibit marginal returns above the sectoral benchmark, and are therefore consistent with tighter capital constraints.

This classification allows us to characterize both the direction and the magnitude of distortions, and to examine how capital misallocation interacts with financial incentives in shaping innovation outcomes.

Subsidies for adopting new technologies are proxied using firm-level information on public subsidies targeted to technology investment. The variable s_i captures the value of technology-specific incentives received by firm i in 2020–2021. As detailed in the data section, these include policy instruments such as the *Credito d'imposta per beni strumentali*, *Nuova Sabatini*, *Patent Box*, and the *Credito d'imposta Mezzogiorno*, all of which are explicitly designed to support technological upgrading and capital modernization. Such instruments are consistent with a broad class of innovation policies aimed at relaxing financing constraints and stimulating firms' investment in new technologies (Howell (2017)). Technology adoption z_i is measured by the firm's reported expenditure (in euros) on digital and advanced technologies in 2021—covering areas such as IoT, robotics, cloud computing, AI, cybersecurity, and 3D printing. The type of innovation captured in the data consists of the adoption of advanced production technologies (e.g., robotics, automation systems, cloud computing, artificial intelligence, cybersecurity, and 3D printing). These technologies enhance both productive efficiency and the perceived and functional quality of the firm's output—including precision, durability, compatibility, and compliance with technical standards. In the model, this maps directly into the vertical quality attribute z_i , which enters consumer utility as a demand shifter and raises willingness to pay, thereby increasing demand for the firm's variety.

We then estimate a set of regression models linking capital misallocation and subsidies to technology adoption. Given the large mass of zeros in technology adoption expenditure z_i (many firms do not adopt at all), the decision to adopt is naturally modelled as a two-part process consisting of a participation decision (extensive margin) and a positive expenditure decision conditional on adoption (intensive margin). The benchmark specification is therefore a Cragg (1971) hurdle model, which allows the two margins to be driven by potentially different mechanisms and covariates. This approach is particularly suitable here because it explicitly separates the binary choice of whether to adopt advanced production technologies from the intensity of adoption, thereby avoiding the restrictive assumptions of single-equation models such as Tobit. Formally:

$$\begin{cases} P(z_i > 0) = \Phi(\alpha_0 + \alpha_1 s_i + 1/\psi_i + \mathbf{v}_i + u_i) \\ z_i | z_i > 0 = \beta_0 + \beta_1 \tau_i + \beta_2 s_i + \beta_3 (\tau_i \cdot s_i) + 1/\psi_i + \mathbf{v}_i + \varepsilon_i, \end{cases} \quad (20)$$

where v_i includes regional and sectoral fixed effects, and u_i, ε_i are error terms.

These specifications allow us to characterize the relationship between capital misallocation, policy support, and technology adoption, and to assess whether the association between subsidies and adoption varies systematically with the degree of distortions faced by firms. This is consistent with evidence that the impact of innovation subsidies may vary across firms depending on their underlying constraints [Howell \(2024\)](#). Firms facing higher capital distortions tend to exhibit lower levels of technological investment, while access to technology-specific incentives increases both the probability and the intensity of adoption. These empirical patterns are interpreted through the lens of the theoretical framework developed in the paper (Testable implications 1 and 2), which provides discipline on the expected sign and interaction between distortions, subsidies, and adoption decisions. Accordingly, the estimates should be viewed as documenting conditional relationships consistent with the model’s mechanisms rather than causal effects in a strict experimental sense. This is consistent with models in which financial frictions reduce firms’ incentives and ability to invest in innovation, thereby slowing productivity dynamics [Lopez-Martin \(2017\)](#).

Results, reported in Table [4](#), confirm the model’s mechanisms. In the first column, capital distortions are negatively and significantly associated with the probability of adoption but not with the level of investment conditional on adoption, consistent with distortions primarily affecting entry into technological upgrading rather than the intensity of investment once adoption occurs. More broadly, frictions affecting firm dynamics have been shown to hinder the adoption of new technologies and slow reallocation towards more efficient producers [Bergoeing et al. \(2016\)](#). Subsidies increase the likelihood of adoption, while the interaction term is negative and significant, suggesting that distortions attenuate the effectiveness of financial support on the extensive margin. This is in line with evidence that distortions affecting more productive firms can generate disproportionately large aggregate losses, thereby weakening the effectiveness of policy interventions [Cirera et al. \(2020\)](#). For inefficiently large firms (Column 2), distortions are not significant in the selection stage but positively related to the adoption level. In column 2, the interaction term is positive, while in column 3 it is negative, which is consistent with the model’s mechanism whereby subsidies strengthen the effect of distortions effect. For inefficiently small firms (Column 3), distortions are negative and significant in both stages, confirming that financial frictions limit both the probability and intensity of adoption. This pattern is consistent with evidence that policy incentives may lead to inefficient allocation responses when firms face heterogeneous constraints [Xu et al. \(2024\)](#) and with evidence that the effectiveness of public support depends on firm-level conditions and may weaken in environments where underlying constraints are more severe [Gelabert et al. \(2009\)](#).

4.1 Robustness

To provide a more robust analysis we complement the Hurdle model with a simple OLS and a Heckman estimation, both controlling for region, sector and firm-size fixed effects. To assess the robustness of our findings, we complement the hurdle model with two alternative specifications. First, we report OLS estimates on the full sample (and on the positive subsample) as a simple linear benchmark; these estimates help verify that the main results are not driven by the specific functional form or distributional assumptions of the two-part model. Second, we estimate a [Heckman \(1979\)](#) selection model, which explicitly accounts for possible correlation between the unobservables driving the partici-

pation decision and the intensity of adoption. This specification allows us to test whether selection bias affects our inferences on the intensive margin and provides a further check on the conditional relationships documented by the hurdle model.

Table 5 reports the OLS estimates for the full sample (Column 1) and for the two subsamples of firms: inefficiently large ($\tau_i > 0$) (Column 2) and inefficiently small ($\tau_i < 0$) firms (Column 3). Across all columns, the results are broadly consistent with the model's core predictions. In the full sample, capital misallocation is negatively and statistically significantly associated with technology adoption, consistent with the idea that financial distortions are linked to lower investment in new technologies. Innovation subsidies are positively and significantly associated with adoption, suggesting that policy support is correlated with greater technology investment. The interaction term between distortions and subsidies is negative and significant, indicating that the association between subsidies and adoption weakens in more distorted environments. $1/\psi_i$ enters positively and significantly, consistent with more productive firms being more likely to adopt new technologies.

Among inefficiently large firms, the coefficient on τ_i turns positive but remains weakly significant, suggesting that within inefficiently large firms distortions may, to some extent, coincide with relatively greater capital availability that can still support technology investment. Subsidies remain positively correlated with z_i , and the interaction term becomes positive, pointing to a potential complementarity between financial support and inefficiently large firm status. Even for inefficiently small firms the theoretical predictions are fully confirmed: higher distortions strongly and significantly reduce technology adoption, while subsidies promote it, but their interaction is negative and significant, implying that financial support becomes less effective in inefficiently small firms. In this group, the coefficient on $1/\psi_i$ is smaller and often statistically insignificant, suggesting that productivity alone is insufficient to offset financial frictions.

Finally, Table 6 presents Heckman selection model estimates used as a robustness check to the hurdle specification. Results are highly consistent: While subsidies are linked to an higher probability to innovate for all firms, distortions have the exactly expected direction for all three columns. In column 1, the full sample, the effect of distortions on intensive margin of adoption is negative and highly significant, in the second column is positive and highly significant, indicating that firms that benefit from capital distortions, the inefficiently large firms, are linked to a higher intensive margin, while the third column, that shows the inefficiently small firms (those who are capital constrained), exhibit the negative and significant effect of distortions on innovation.

5 Aggregate loss from misallocation

We now turn to the aggregate implications in order to compute the counterfactual gains implied by the model. To do so, we need to recover two sector-specific objects: the productivity cutoff governing firm selection and the extent to which distortions are systematically correlated with firm productivity.

We begin by constructing, for each firm, an inverse measure of productivity based on estimated total factor productivity. This index is then aggregated at the sector level and forms the basis for recovering the structural moments required by the model. The first object is the sectoral productivity cutoff. In the theoretical framework, each sector is characterised by a marginal surviving firm whose productivity level solves a closed-form

condition linking market competition and the distribution of firm efficiencies. Following the empirical strategy developed in Corcos et al. (2012) and related contributions, we exploit the proportional relationship between the cutoff and observed sectoral price levels. To implement this, we first estimate the shape parameter of the Pareto distribution governing firm costs. We compute unit input requirements as the inverse of total factor productivity, normalize them by the sector-specific mean to obtain standardized costs, and then apply a transformation to correct for truncation (since only surviving firms are observed) and variable markups: specifically, we compute an adjusted cost measure for each firm by dividing its standardized cost by twice the sector’s maximum standardized cost minus the firm’s own value.⁷ This adjusted measure is then used to construct the empirical cumulative distribution function within each sector. We regress the log of this empirical CDF on the log of the adjusted costs; the slope of the regression yields our estimate of the Pareto shape parameter. With this shape parameter in hand, we compute the sectoral cutoff by multiplying a function of the shape parameter by the average producer price in that sector.⁸

The second object required by the model is the degree of systematic misallocation. For each sector, we estimate the elasticity of distortions with respect to productivity, which corresponds to the parameter χ in the theoretical framework. Empirically, this elasticity is obtained from sector-specific regressions of the logarithm of firm-level distortions on the logarithm of firm productivity. The resulting coefficient captures whether more productive firms face systematically higher or lower distortions within a sector. Together, the estimated cutoff ψ_d and distortion elasticity χ provide the sufficient statistics needed to evaluate the model-implied counterfactual changes in aggregate technology when the distortion–productivity correlation is shut down.

Nevertheless, by combining micro-level estimates with the equilibrium structure of the model, the analysis provides informative orders of magnitude on the potential role of systematic misallocation in shaping sectoral technology outcomes. Accordingly, the estimated gains should be viewed as indicative of the economic relevance of the mechanism rather than as point estimates of achievable policy effects.

These estimates, together with observed sectoral technology $\bar{z}$, allow us to compute how average aggregate technology would change under a counterfactual scenario in which the correlation between distortions and productivity is shut down ($\chi_s = 0$). Table 7 reports the full set of results. A first inspection of the one-digit results already reveals a clear sectoral gradient in the magnitude of the counterfactual gains. Traditional manufacturing sectors such as food, textiles and wood display the lowest improvements, while gains increase progressively when moving toward more capital-intensive activities and modern service sectors. In particular, ICT, finance and real estate activities, together with other advanced services, exhibit the largest potential improvements, with gains approaching or exceeding 20 percent.

A clear pattern emerges from these estimates. Sectors with higher estimated productivity cutoffs tend to display larger gains, suggesting that systematic distortions are more costly in environments where only relatively productive firms operate at scale. While these descriptive patterns do not establish causality, they already point toward a struc-

⁷The transformation is given by $\hat{c}_{i,s} = \frac{c_{i,s}}{2c_{\max,s} - c_{i,s}}$, where $c_{i,s}$ is the standardized unit input requirement for firm i in sector s , and $c_{\max,s}$ is the sector’s maximum standardized value. This adjustment recovers the underlying Pareto distribution by accounting for the linear pricing structure and selection effects in the model.

⁸Prices are sourced from EU KLEMS following Timmer et al. (2007).

tural dimension related to the importance of capital in production, which we explore more formally below.

The one-digit counterfactual results suggest that systematic misallocation may act as an important brake on aggregate technology, and that this effect is not evenly distributed across sectors. The estimated gains range between approximately 11 and 21 percent across broad sectors, with the largest improvements observed in ICT, finance and real estate activities, as well as in other service sectors characterized by relatively high productivity cutoffs. An immediate interpretation consistent with the model is that sectors in which production relies more heavily on capital accumulation — whether physical or intangible — are more exposed to distortions operating through capital wedges. In those environments, preventing high-productivity firms from expanding generates disproportionately large aggregate losses. This intuition motivates the next step of the analysis, where we explicitly relate the sectoral gains to observable measures of capital intensity.

To capture these mechanisms more directly, we move to a finer two-digit classification and relate the counterfactual gains to observable sectoral characteristics. This shift in granularity allows us to assess whether unrealized technological capacity is systematically associated with capital intensity and the structural importance of capital in production, thereby providing a structural interpretation of the aggregate patterns documented above. In addition, to provide a broader validation of our analysis and observe sectoral patterns, we draw on sectoral data from EU-KLEMS [9](#) to characterize the production structure of Italian two-digit industries. We thus obtain measures of real capital stocks (tangible and intangible) and value added, which we use to construct sectoral capital intensity as the capital-to-value-added ratio averaged over the period 2015–2019. These structural measures are merged with our sector-level counterfactual gains to assess whether unrealized technological potential is systematically associated with persistent differences in capital deepening across industries.

We provide complementary evidence linking the counterfactual gains to an observable proxy of sectoral technology. In particular, we exploit data from the International Federation of Robotics (IFR) to construct measures of robot adoption at the two-digit sector level. Robot intensity is defined as the log of sectoral robot stock normalized by the yearly average, thereby capturing relative differences in technology adoption across industries within each year.

We then relate log gains from reallocation to sectoral robot intensity in a specification that absorbs year fixed effects, thus focusing on within-year cross-sector variation. Robot intensity is constructed from IFR data as the logarithm of sectoral robot stock normalized by the yearly average, that is, $\ln\left(\frac{R_{s,t}}{\bar{R}_t}\right)$, where $R_{s,t}$ denotes the total stock of robots in sector s and year t , and $\bar{R}_t$ is the average robot stock across sectors in year t . This normalization removes aggregate time trends and isolates relative differences in technology adoption across industries.

Figure [9](#) shows a positive and statistically significant relationship: sectors with higher robot intensity display systematically larger gains from reallocation. The coefficient reported in Figure [9](#) is obtained from a regression of log gains on robot intensity with year fixed effects: $\ln(\text{gains}_{s,t}) = \beta \ln\left(\frac{R_{s,t}}{\bar{R}_t}\right) + \gamma_t + \varepsilon_{s,t}$.

It therefore captures the within-year cross-sector elasticity of gains with respect to relative robot adoption, net of common time-specific shocks. The evidence suggests

⁹Data are taken from <https://euklems-intanprod-llee.luiss.it/download/>, using intangibles dataset for all countries.

that sectors closer to the technological frontier—proxied by higher adoption of industrial robots—are also those in which distortions generate larger aggregate losses. This is consistent with evidence that innovation and productivity are strongly shaped by high-technology environments characterized by knowledge spillovers and dense clusters of innovative activity [Moretti \(2021\)](#). In line with the model, this finding is consistent with the idea that preventing high-productivity firms from expanding is particularly costly in technologically advanced environments. These results provide an additional, data-driven characterization of the sectoral gradient in gains, and motivate the subsequent analysis linking misallocation to structural features of production.

To better characterize the sectoral structure underlying the counterfactual gains, we first examine whether unrealized technological potential is systematically associated with capital intensity at the two-digit level. In the model, distortions operate through the cost of capital, implying that sectors in which production relies more heavily on capital inputs should be more sensitive to systematic misallocation.

We define sectoral capital intensity for each two-digit sector s as average real capital-to-value-added ratio over the period 2015–2019:

Capital Intensity $_s = \frac{K_s}{VA_s}$, where K_s denotes the total real capital stock (tangible and intangible) and VA_s is real value added. Averaging over multiple pre-2021 years allows us to capture persistent structural differences in production structure rather than short-run fluctuations.

We then relate log gains from capital reallocation to sectoral log capital intensity in a cross-sectional regression across two-digit industries. [Figure 10](#) documents a positive and statistically significant relationship between sectoral capital intensity and gains from reallocation. Sectors characterized by higher capital intensity—measured as a larger capital stock relative to value added—display systematically larger counterfactual improvements in aggregate technology once the systematic component of misallocation is removed. Importantly, this cross-sector relationship provides a structural interpretation of the patterns already visible in the one-digit results discussed above. The sectors that exhibited the largest counterfactual gains are also those characterized by relatively high capital-to-value-added ratios in EU-KLEMS data. Conversely, sectors with lower capital intensity display more moderate gains. The positive slope observed in [Figure 10](#) therefore rationalizes the earlier descriptive evidence and suggests that differences in capital deepening are a key dimension shaping the magnitude of allocative inefficiency across industries.

This consistency across levels of aggregation strengthens the interpretation that the gains identified by the counterfactual exercise are not driven by sector-specific noise, but instead reflect systematic variation in the economic cost of capital misallocation across production structures. This evidence is consistent with the model’s mechanism: distortions that operate through capital wedges are quantitatively more costly in industries where capital plays a more prominent role in production. The magnitude of aggregate technology losses therefore depends on the structural intensity of capital in the production process.

In such industries, distortions that prevent efficient firms from expanding translate into amplified aggregate technology losses. Improving allocative efficiency is therefore particularly consequential in sectors where production relies heavily on embodied capital and where allocative dispersion is more pronounced.

6 Conclusion

This paper studies how capital misallocation and innovation subsidies jointly shape firms' technology adoption decisions and aggregate technological performance. The analysis combines a simple structural framework with firm-level and sector-level evidence to identify both microeconomic and aggregate channels.

At the firm level, distortions in capital allocation reduce technology adoption, and their interaction with subsidies is negative. While subsidies increase adoption on average, their effectiveness declines as distortions intensify. In environments characterized by tighter capital constraints, financial incentives do not offset distortions and may amplify their adverse effects. The hurdle estimates indicate that misallocation primarily affects the decision to adopt, whereas subsidies operate mainly on the extensive margin. These findings are consistent with the model's prediction that the interaction between distortions and subsidies weakens technological upgrading when capital is inefficiently allocated.

At the aggregate level, distortions are systematically correlated with productivity within sectors. Shutting down this distortion–productivity correlation generates economically meaningful counterfactual increases in average sectoral technology, typically in the range of 10–20 percent. In addition, sectors closer to the technological frontier—proxied by higher robot adoption—exhibit systematically larger gains from reallocation, indicating that the aggregate cost of misallocation is disproportionately concentrated in more technologically advanced industries. Moreover, the gains from reallocation are disproportionately concentrated in sectors characterized by higher capital intensity. This pattern is consistent with the structural mechanism of the model: when production relies more heavily on embodied capital, wedges that prevent more productive firms from expanding translate into amplified aggregate losses.

These results should be interpreted in light of some limitations. The empirical analysis identifies systematic associations between distortions, subsidies, and technology adoption, but does not aim to establish fully causal effects of reallocative reforms, since the counterfactual exercise relies on model-based extrapolation of estimated parameters rather than on policy-induced variation in allocation.

Future research could extend the analysis by exploring alternative measurements of the distortion–productivity correlation and assessing the sensitivity of counterfactual gains to different identification strategies and calibration choices.

Taken together, the evidence shows that systematic capital misallocation depresses both firm-level technology adoption and aggregate technological performance, and that innovation policies cannot be evaluated independently of the allocative environment in which they operate. Improving within-sector allocation emerges as a central condition for the effectiveness of subsidies and for restoring aggregate technological growth.

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Descriptive Statistics

	$\log(\text{VA})$	$\log(K)$	L
Productivity quartiles			
0–25%	14.99	16.39	82
25–50%	15.50	16.25	90
50–75%	16.00	16.85	108
75–100%	16.09	16.82	61
Total	15.73	16.61	85

Table 1: **Production inputs by productivity quartiles.** The table reports average firm-level characteristics across quartiles of productivity. $\log(\text{VA})$ denotes the logarithm of real value added, $\log(K)$ is the logarithm of the capital stock, and L represents the average number of workers. All statistics are computed as means within each quartile of the firm-level productivity distribution.

	s_i	z_i	$\log(\text{VA})$	$\log(K)$	L
Misallocation quartiles					
0–25%	595357	208037	15.76	15.72	91
25–50%	1918720	307835	15.75	16.13	84
50–75%	715049	246358	15.65	16.48	89
75–100%	3152786	59843	15.76	17.35	77
Total	1595346	205521	15.73	16.61	85

Table 2: **Production inputs by capital misallocation quartiles.** The table reports average firm-level characteristics across quartiles of capital misallocation. s_i denotes the average amount of subsidies received (in euros), z_i (defined in Section 3) is the average value of technology investment expenditures (in euros).

	τ_i	$z_i\%$	z_i	s_i	$\log(\text{VA})$	$\log(K)$
Food, textiles, wood and related manufacturing	-0.68	24.86	40359	81726	15.43	15.85
Chemicals, pharma, metals, and related industries	-1.13	35.91	317,822	165,992	15.71	16.65
Transport equip., utilities, waste-related activities	0.22	14.57	151,485	7,421,862	15.93	17.27
Construction, trade and related activities	-0.64	25.91	152,559	1,020,799	15.40	16.21
Transport, accommodation, publishing	-0.73	30.97	274,348	145,609	15.99	17.08
ICT, finance, real estate	-1.11	35.58	478,950	223,518	16.15	16.82
Professional & administrative services	-0.38	30.45	88,696	91,316	15.72	15.99
Support, public, health, education	-0.40	14.18	22,281	2,833,796	15.30	16.43
Arts, other services, households	0.02	20.53	34,011	6,394,018	16.05	18.58
Total	-0.63	28.43	203,916	1,572,288	15.72	16.80

Table 3: **Technology investment and firm characteristics by sector.** The table reports sectoral averages of key firm-level variables. τ_i denotes the average firm level distortion measure. $z_i\%$ is the share of technology investment expenditures as a percentage of total investment.

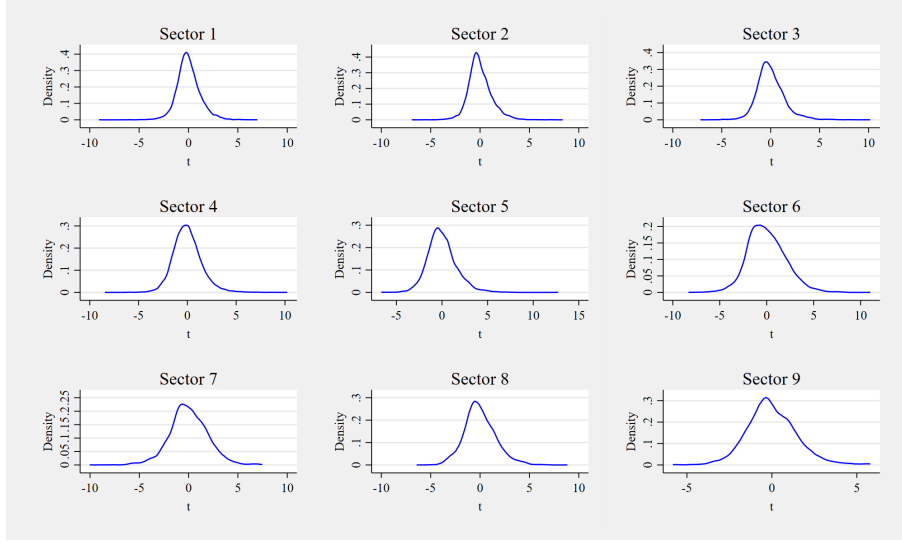


Figure 2: Density of Firm-Level Misallocation. This figure presents the kernel density estimation of misallocation across sectors aggregated at the one-digit level based on two-digit ATECO intervals. Sector codes 1 to 9 correspond respectively to ATECO 10–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, 80–89, and 90–99.

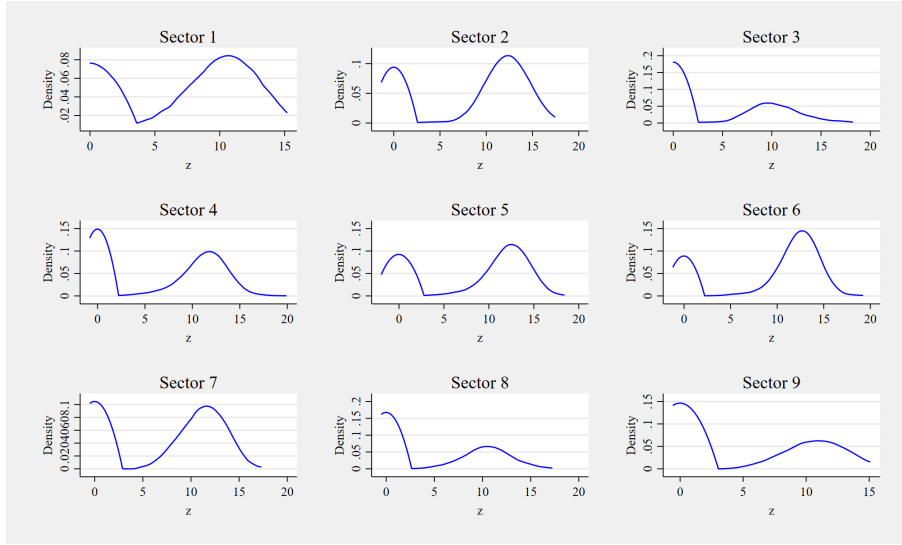


Figure 3: Density of Technology Adoption (Log). This figure presents the kernel density estimation of technology adoption across sectors aggregated at the one-digit level based on two-digit ATECO intervals. Sector codes 1 to 9 correspond respectively to ATECO 10–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, 80–89, and 90–99.

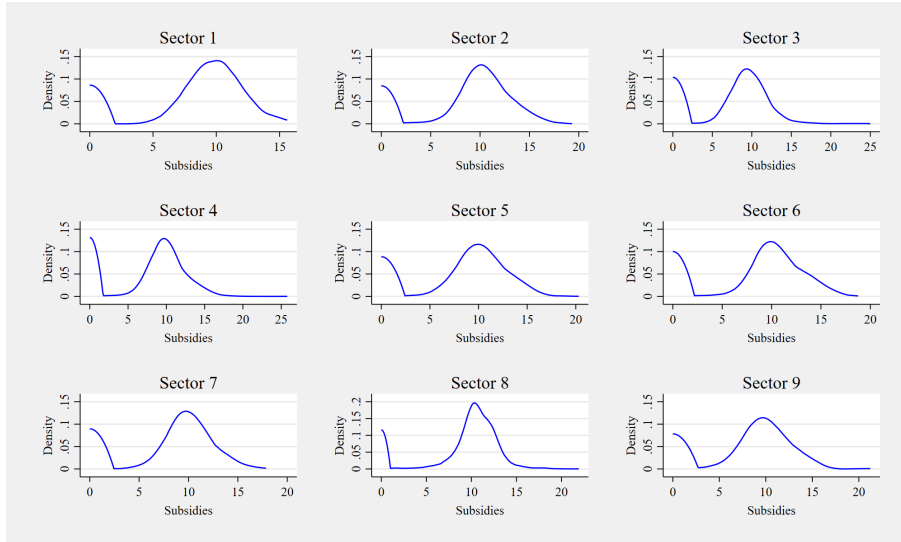


Figure 4: Density of Aid (Log). This figure presents the kernel density estimation of Aid across sectors aggregated at the one-digit level based on two-digit ATECO intervals. Sector codes 1 to 9 correspond respectively to ATECO 10–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, 80–89, and 90–99.

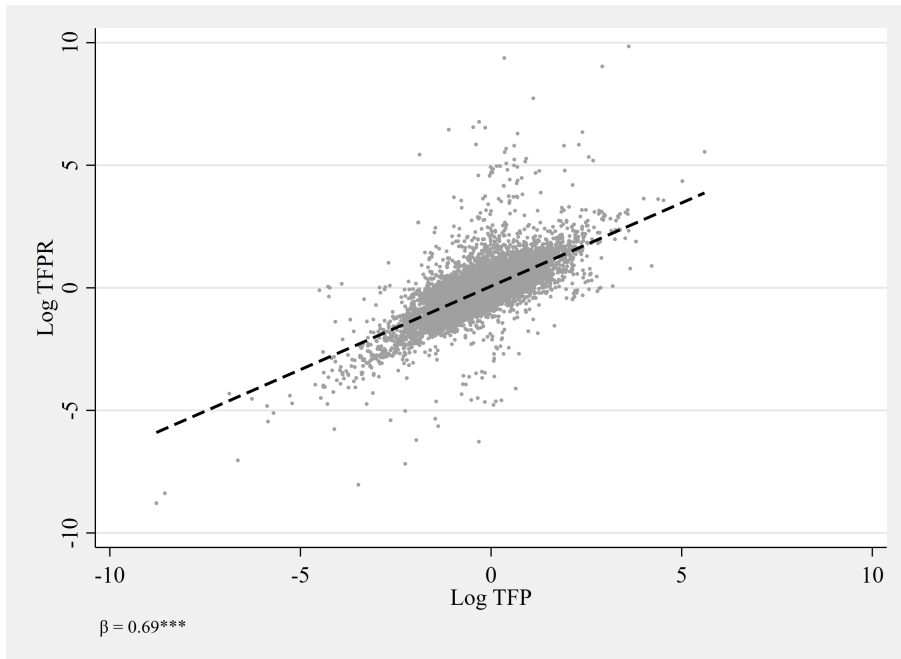


Figure 5: **Elasticity of Distortions.** The figure plots firm-level log TFPR distortions against log TFP. The solid line represents the fitted relationship. The reported coefficient is obtained from a regression including sector and year fixed effects, with standard errors clustered at the sector level.

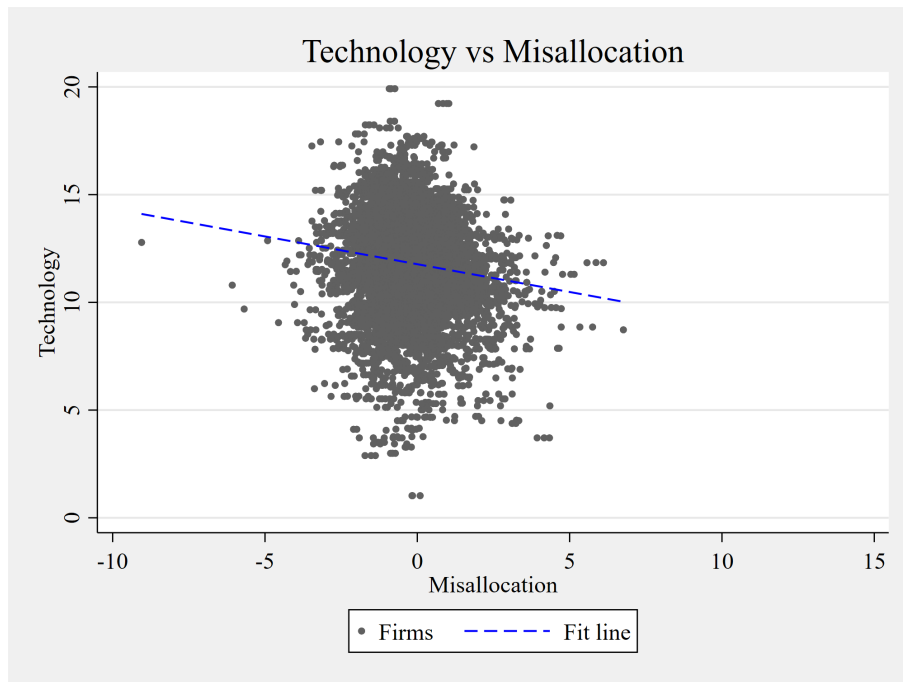


Figure 6: Technology vs Misallocation

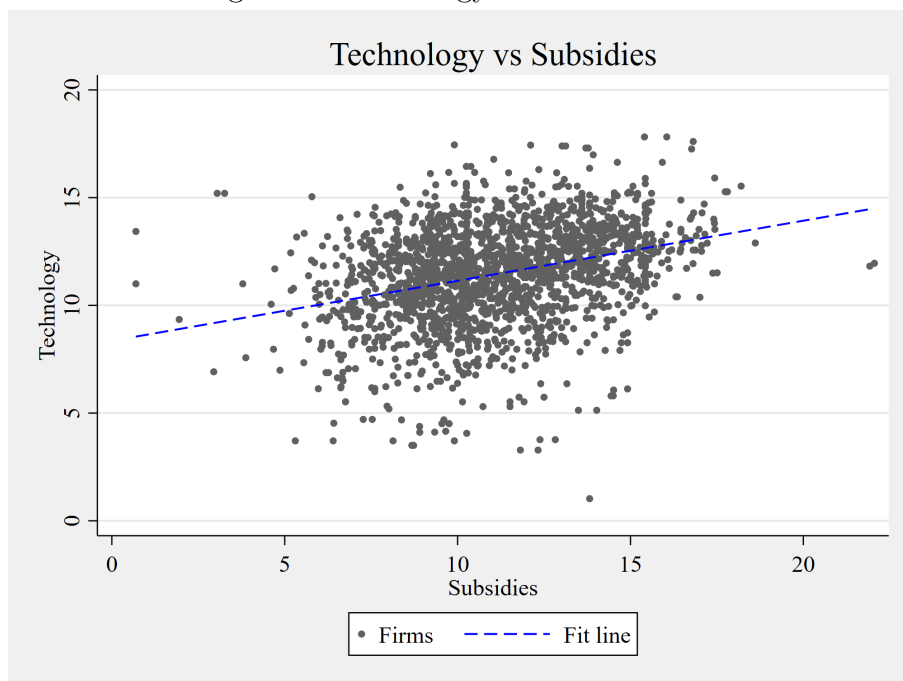


Figure 7: Technology vs Subsidies

Figure 8: Bivariate relationships between technology, misallocation, and subsidies.

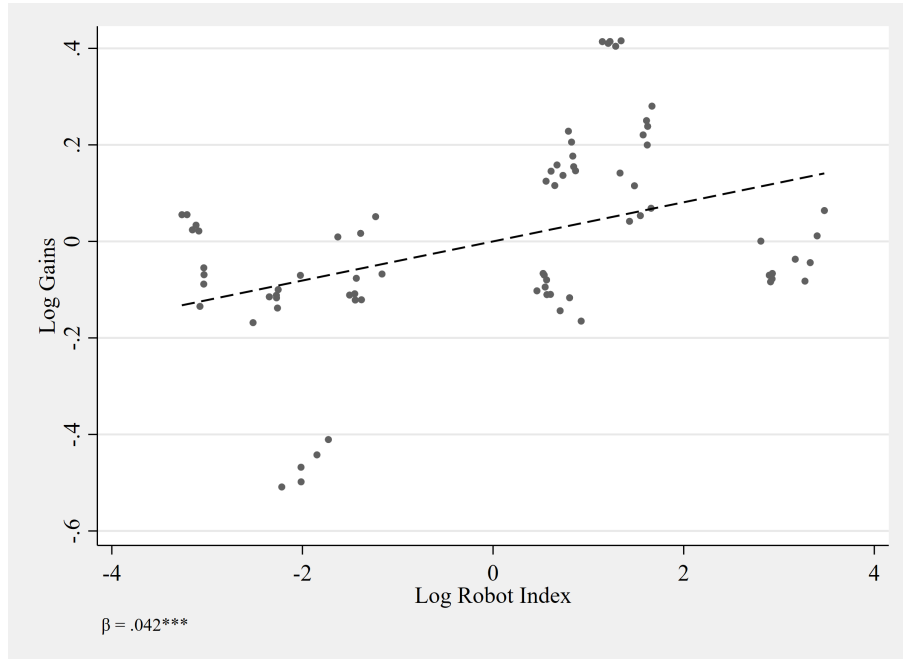


Figure 9: **Robotization and Gains from Reallocation.** The figure plots the relationship between log gains from reallocation and sectoral robot intensity, both demeaned by year fixed effects. Robot intensity is measured as the log of the sectoral robot stock normalized by the yearly average. The solid line reports the linear fit from a regression of residualized gains on residualized robot intensity.

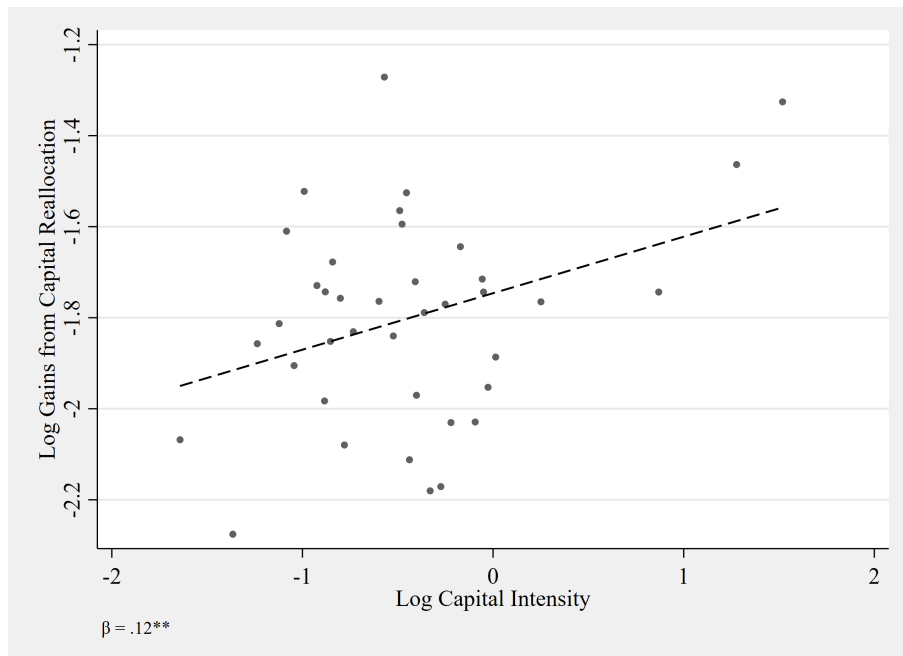


Figure 10: **Capital Intensity and Gains from Capital Reallocation.** The figure plots the cross-sector relationship between log gains from capital reallocation and sectoral log capital intensity. Capital intensity is measured as the average capital-to-value-added ratio. The solid line reports the linear fit from a cross-sectional regression across sectors.

	(1)	(2)	(3)
<i>Outcome equation</i>			
τ_i	0.00256 (0.0176)	0.0626** (0.0245)	-0.0706** (0.0285)
s_i	-0.0157** (0.00779)	-0.0108 (0.0122)	-0.00444 (0.0164)
$\tau_i s_i$	-0.00885 (0.00573)	0.0140 (0.00994)	0.00177 (0.0132)
$1/\psi_i$	0.447*** (0.0816)	0.685*** (0.104)	0.386*** (0.140)
Constant	10.88*** (0.253)	11.62*** (0.318)	9.441*** (0.410)
<i>Selection equation</i>			
τ_i	-0.0220*** (0.00617)	0.0112 (0.00939)	-0.0424*** (0.00989)
s_i	0.0146*** (0.00280)	0.0220*** (0.00473)	0.0228*** (0.00567)
$\tau_i s_i$	-0.00292* (0.00170)	0.00907*** (0.00348)	-0.00819** (0.00368)
$1/\psi_i$	0.0536** (0.0261)	0.134*** (0.0366)	0.0453 (0.0439)
Constant	-1.336*** (0.0880)	-1.211*** (0.115)	-1.535*** (0.145)
Constant	0.635*** (0.0150)	0.618*** (0.0190)	0.553*** (0.0243)
N	13302	7247	6055
Pseudo- R^2	0.122	0.138	0.125

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: **Benchmark Table:** Hurdle Model following equation (19). Selection equation models the probability of positive z_i ; outcome equation models intensity conditional on adoption. Dependent variable is z_i results shown for all firms (column 1), inefficiently large firms (column 2), and inefficiently small firms (column 3).

	(1)	(2)	(3)
τ_i	-0.0642*** (0.0160)	-0.00986 (0.0530)	-0.149*** (0.0395)
$1/\psi_i$	0.174*** (0.0563)	0.394*** (0.0904)	0.111 (0.0807)
s_i	0.0353*** (0.00811)	0.0557*** (0.0154)	0.0481*** (0.0155)
$\tau_i \times s_i$	-0.0103*** (0.00374)	0.0234** (0.00969)	-0.0157** (0.00710)
Constant	1.672*** (0.269)	2.350*** (0.394)	1.013*** (0.342)
N	13302	7247	6055
Adj. R^2	0.162	0.186	0.124
Sector FE	✓	✓	✓
Region FE	✓	✓	✓
Size FE	✓	✓	✓

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: **Robustness check 1.** OLS estimates by firm type. Dependent variable is z_i . Column (1) refers to the full sample of firms; Column (2) to inefficiently large firms; and Column (3) to inefficiently small firms. All specifications include $1/\psi_i$, innovation subsidies, and their interaction with capital distortions, with fixed effects by 2-digit sector, region, and firm size class.

	(1)	(2)	(3)
τ_i	-0.302*** (0.0422)	0.277*** (0.0921)	-0.652*** (0.0957)
Constant	11.08*** (0.526)	11.92*** (0.738)	11.30*** (1.067)
z_i^{dummy}			
s_i	0.0185*** (0.00252)	0.0183*** (0.00306)	0.0112*** (0.00390)
Constant	-0.726*** (0.0694)	-0.949*** (0.0199)	-1.135*** (0.0226)
ath ρ	0.0324 (0.145)	0.0509 (0.194)	0.0940 (0.256)
ln σ	0.910*** (0.0149)	0.970*** (0.0200)	0.952*** (0.0304)
Observations	14,670	7,848	6,822

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: **Robustness check 2.** Heckman selection model estimates. Dependent variable is z_i while columns setup replicates the one above in Table 7. First stage estimates the effect of s_i on the decision to invest; second stage estimates the effect of τ_i on investment value.

Sector	ψ_d	χ	Z^{gain} (%)
Food, Textile, Wood and Related Manufacturing Industries	1.18	0.69	11.56
Chemical, Metal and Machinery Industries	1.20	0.74	14.96
Heavy Manufacturing and Utility-Related Activities	1.23	0.78	16.37
Construction, Trade and Related Activities	1.26	0.67	17.53
Transport, Accommodation and Publishing-Related Activities	1.33	0.63	18.08
ICT, Finance and Real Estate Activities	1.30	0.68	20.95
Professional and Administrative Services	1.32	0.67	17.27
Support, Public and Health Services	1.24	0.65	13.21
Arts, Other Services and Household Activities	1.32	0.72	19.29

Table 7: **Sectoral Cutoffs, Distortion Elasticity, and Reallocation Gains.** The table reports the estimated sectoral cutoff ψ_d , the distortion elasticity parameter χ , and the implied reallocation gains Z^{gain} expressed in percentage terms across one-digit sectors.

Farm Size, Climate Adaptation, and Unequal Climate Damages across Countries

A joint work with Tasso Adamopoulos, Hyungju Henry Kim, Duc Nguyen, and Diego Restuccia

Abstract

We examine how climate damages differ across countries at different stages of development through differences in farm structure and adaptation. Across countries, projected declines in potential yields are large and heterogeneous, but not systematically larger in poorer economies. What differs sharply with development is agricultural structure: low-income countries have smaller farms, higher agricultural employment, lower adaptive capacity, and greater food insecurity. Using evidence from Italy, we document that smaller farms invest less in adaptation technologies, suffer larger productivity losses from heat exposures, and that adaptation attenuates these losses. We incorporate this evidence into a structural transformation model with heterogeneous farm sizes, climate-induced declines in agricultural productivity, and endogenous adaptation investment. Calibrated to Italian farm-level and aggregate data, the model implies that, for a common climate shock, poorer economies adapt less, generating larger realized agricultural productivity losses, slower reallocation of labor out of agriculture, higher food insecurity, and lower aggregate labor productivity. In our common productivity growth scenario to 2050, low-income economies offset 15–17 percent of farm-level losses through adaptation, compared with 66–69 percent in high-income economies. Under a 30 percent damage scenario, low-income economies have agricultural employment and food insecurity 8.3 and 5.9 percentage points higher, and aggregate labor productivity 11.5 percent lower relative to the no-damage path. Climate damages slow structural transformation and weaken convergence in aggregate productivity.

Keywords: Climate change, productivity, agriculture, farm size, adaptation technology, structural transformation, food insecurity.

JEL classification: E14, O11, O13, O14, O4, O5, Q1, Q54.

1 Introduction

Climate change is projected to reduce agricultural productivity in many parts of the world. A central question is whether these losses will widen differences in living standards across countries. The answer depends not only on where climate shocks occur, but also on how economies absorb them. Our cross-country evidence shows that while projected declines in potential yields are large and highly dispersed, they are not systematically related to countries' levels of aggregate labor productivity. What does vary sharply with development is the economic environment in which these shocks arrive: less developed countries feature much larger shares of the population engaged in agriculture, operate much smaller farms, exhibit lower adaptive capacity, and face much higher food insecurity. As a result, similar climate shocks can generate very different realized productivity losses and aggregate consequences across countries.

A key reason for these unequal consequences is climate adaptation. Farms can mitigate climate damages by changing inputs and practices—for example through irrigation, improved varieties, and management—but adaptation is costly and uneven ([Deschênes and Greenstone, 2007](#); [Burke and Emerick, 2016](#)). We argue that the farm-size distribution is a proximate determinant of adaptation capacity. Agriculture in low-income countries is dominated by small farms ([Adamopoulos and Restuccia, 2014](#)). If small farms adapt less and therefore suffer larger realized losses from a common climate shock, then developing countries will face larger declines in agricultural productivity, greater food insecurity, and slower reallocation of labor out of agriculture. This mechanism is distinct from, and complementary to, recent work emphasizing limits to adaptation through sectoral reallocation in the presence of subsistence needs ([Gollin et al., 2007](#); [Nath, 2025](#)) and general-equilibrium channels operating through trade and comparative advantage ([Costinot et al., 2016](#)).

We document a set of empirical facts that motivate this mechanism. Across countries, projected climate-induced losses in potential yields are substantial but not systematically concentrated among poor countries. At the same time, poorer economies rely much more on agriculture, have much smaller farms, and exhibit both lower adaptive capacity and higher food insecurity.

Countries with larger farms also display systematically higher adaptive-capacity indexes. These patterns suggest that unequal climate damages across countries may arise less from unequal exposure per se than from differences in agricultural structure and the ability to adapt.

We then turn to farm-level evidence from Italy, which provides a useful laboratory because it combines rich farm microdata with substantial heterogeneity in farm size and climate exposure. Using farm-level data matched to local weather, we show that HeatExposures reduce farm productivity and that these losses are substantially larger for smaller farms. Smaller farms also use adaptation technologies—measured by drip irrigation—at much lower rates. Finally, using variation in EU environmental and agro-climatic investment funds as an instrument, we show that adaptation causally attenuates the productivity impact of HeatExposures. Taken together, the micro evidence implies that farm size shapes realized climate damages precisely through differences in adaptation.

Motivated by these facts, we develop a model of structural transformation with heterogeneous farm sizes, climate damages, and endogenous investment in adaptation technology. The model builds on [Gollin et al. \(2002\)](#) and [Restuccia et al. \(2008\)](#) and incorporates farm-size heterogeneity as in [Adamopoulos and Restuccia \(2014\)](#). Climate change reduces farm productivity, and farms choose adaptation investment subject to convex costs. We discipline the adaptation technology with the farm-level estimates and calibrate the remaining parameters to Italian micro and aggregate data. We use the calibrated model to quantify the aggregate consequences of climate damages across economies at different stages of development. The experiments deliver three main results. First, for a common agricultural productivity shock, poorer economies adapt substantially less, so realized agricultural productivity losses are much larger. In our common productivity growth to 2050 exercises, high-income economies offset about two-thirds of average farm-level losses through endogenous adaptation, whereas low-income economies offset only about 15–17 percent. Second, these differences in adaptation translate into much larger macroeconomic and welfare effects in poor countries. Under a 30 percent climate-damage scenario, low-income economies end up with agricultural employment 8.3 percentage points above

their no-damage path, food insecurity 5.9 percentage points higher, and aggregate labor productivity 11.5 percent lower; under a 70 percent damage scenario, the corresponding effects are 22.5 percentage points higher agricultural employment, 13.2 percentage points higher food insecurity, and 30.9 percent lower agricultural productivity. The corresponding effects in high-income economies are close to zero. Third, climate damages slow structural transformation and weaken convergence in aggregate labor productivity because poorer countries both rely more heavily on agriculture and realize larger losses within agriculture.

Our paper relates to several strands of literature. First, it connects to empirical work on climate and agriculture that estimates how temperature shocks affect yields, revenues, and farm performance ([Deschênes and Greenstone, 2007](#); [Burke and Emerick, 2016](#)). We contribute by documenting systematic heterogeneity across farms in both adaptation and realized climate damages, and by showing how these micro differences map into aggregate outcomes in general equilibrium. Second, the paper connects to the literature on farm size, land misallocation, and cross-country agricultural productivity differences ([Adamopoulos and Restuccia, 2014](#); [Chen et al., 2022, 2023](#)). Our contribution is to show that the farm-size distribution matters not only for average productivity, but also for climate resilience. Third, our analysis builds on the macro-development literature on structural transformation and the food problem ([Gollin et al., 2002, 2007](#); [Restuccia et al., 2008](#); [Herrendorf et al., 2014](#); [Nath, 2025](#)). We show that endogenous adaptation within agriculture is an additional force shaping the speed of reallocation out of agriculture, food insecurity, and convergence. Finally, our paper complements quantitative climate analyses that emphasize trade, geography, and comparative advantage ([Costinot et al., 2016](#)). We focus instead on a within-agriculture mechanism: how farm structure shapes investment in adaptation technologies and, in turn, the realized incidence of climate damages across countries at different levels of development.

The remainder of the paper is organized as follows. Section [2](#) describes the data. Section [3](#) presents the empirical evidence. Section [4](#) develops the model. Section [5](#) discusses the calibration and quantitative results. Section [6](#) concludes.

2 Data

We describe the datasets used for the empirical analysis in the next section. We combine detailed farm-level microdata for Italy with gridded local climate data to study the climate change impact on farm productivity and the adaptation responses at the farm level. We also use global datasets to document cross-country patterns on the extent of agricultural employment, farm-size structure, food insecurity, climate exposure and adaptation capacity.

Italian farm-level microdata (RICA/FADN). Italy is well suited for studying farm-size heterogeneity and climate adaptation because, despite being an advanced country, its agricultural sector exhibits a wide range of farm sizes, with the coexistence of very small farms and large farms. This variation allows us to examine how technology use and climate vulnerability differ across the farm-size distribution. Table 1 provides descriptive evidence from the Italian microdata (RICA) on the distribution of farm sizes, land shares, and productivity by farm-size classes. Consistent with the evidence for the United States (Adamopoulos and Restuccia, 2014), even though most farms are relatively small in size, they account for a small share of operated land, and even though smaller farms have higher average yields (output per unit of land) and capital to land ratios, larger farms are more productive (output per unit of labor).

Our main micro dataset is the Italian Farm Accountancy Data Network (RICA), the Italian component of the EU Farm Accountancy Data Network (FADN/FSDN), administered by CREA.¹ RICA is an annual stratified survey designed to be representative of the population of farms in Italy. The sampling design, with a rotating panel structure, with roughly 25 percent of farms replaced each year, follows the standard FADN methodology and stratifies farms by region, economic size, and production specialization to ensure representativeness across the agricultural sector. Each year the survey covers approximately 11,000 farms. We use the 2008–2021 waves and restrict the sample to crop-producing farms with positive operated land and

¹The Italian Farm Accountancy Data Network (RICA) is part of the EU Farm Accountancy Data Network (FADN). See <https://rica.crea.gov.it> for institutional details.

Table 1: Summary Statistics by Farm Size

Farm size (ha)	Share of farms (%)	Share of land (%)	Value Added per land	Value added per worker	Capital-land ratio
< 1	2.6	0.1	57.396	1.000	16.082
1–5	16.7	1.7	12.337	1.104	5.032
5–10	18.8	4.6	6.976	1.303	3.757
10–20	20.7	9.8	4.492	1.432	2.767
20–50	24.1	25.3	2.601	1.566	2.180
> 50	17.1	58.6	1.000	1.609	1.000

Notes: Farm size bins are defined based on operated land area in hectares. Farm share and land share denote the proportion of farms and total land in each size class. Value added per hectare and the capital-land ratio are normalized relative to the values observed in the largest farm-size class. Value added per worker is normalized relative to the smallest size class. Capital refers to agricultural capital.

non-missing information on key production variables, which are the most relevant for studying HeatExposure and irrigation-based adaptation. The final estimation sample contains approximately 98,000 farm-year observations.

The dataset contains detailed information on production, input use, land operated (hectares), labor, capital, and financial accounts, see Table A.1 for some summary statistics. We construct a real measure of farm productivity following standard approaches in the literature ([Adamopoulos et al., 2022](#); [Chen et al., 2022, 2023](#)). In particular, we assume a decreasing returns to scale farm production function with standard parameter values and data on output and inputs. In order to compute the output and input variables, we use detailed information on farm production by product in physical units to build real agricultural output. For each crop, we compute a unit value as the ratio between the value of sales and the quantity sold, excluding observations with non-positive quantities or values. We then compute the average unit value at the crop level across the entire sample and use this common price to value physical production for all farms and years. By using crop-specific prices that are constant over time, differences in output across farms and years reflect differences in quantities rather than variation in farm-level prices. Real output at the farm-year level is obtained by summing the value of all products evaluated at these crop-level average prices.

Intermediate inputs are constructed as the sum of detailed expenditure categories including fertilizers, pesticides and herbicides, seeds and seedling, feed, forage and bedding, utilities and fuel. To account for price variation over time, intermediate expenditures are deflated using agricultural intermediate input price index from ISTAT. Real value added is then defined as real output net of deflated intermediate inputs. This measure represents the baseline output concept used in the empirical analysis. Capital is measured using balance-sheet information on agricultural fixed capital, which includes machinery, equipment and other assets. In order to obtain a real measure, we use the agricultural capital deflator from ISTAT. Land input is the cultivated agricultural area by the farm in hectares. Baseline farm land size is defined using the first year the farm is observed in the sample, ensuring that it is predetermined relative to potential subsequent climate shocks.

We compute farm-level productivity using the variables defined above, setting $\alpha = 2/3$ and $\gamma = 0.54$:

$$\ln \text{TFP}_{it} = \ln y_{it} - \gamma \left(\alpha \ln \ell_{it} + (1 - \alpha) \ln k_{it} \right),$$

where y_{it} denotes farm real value added, ℓ_{it} farm land, and k_{it} farm capital. In the empirical implementation, output, land and capital are expressed per unit of labor. This normalization allows us to isolate productivity differences across farms after accounting for differences in input intensity.

To capture farm-level adaptation, we use the intensity of drip (micro-) irrigation, measured as $\log(Drip_{it} + 1)$, where $Drip_{it}$ denotes the area equipped with water-saving irrigation technologies. Irrigation is widely studied in the climate-economics literature as an important margin of agricultural adaptation to higher temperatures, drought risk, and water scarcity ([Mendelsohn and Seo, 2007](#); [Taylor, 2022](#)). Within this broader adaptation margin, drip and micro-irrigation represent water-conservation technologies that improve water-use efficiency and can increase farms' resilience to heat and drought stress. Variation in drip-irrigated area therefore provides an observable measure of farms' use of climate-relevant adaptation technologies across the farm-size distribution.

As an instrumental variable for adaptation, we use farm-level receipts of environmentally targeted European Union funds under the Second Pillar of the Common Agricultural Policy. These funds correspond to green and agri-environmental measures designed to promote sustainable production practices. The instrument is constructed as the annual amount of such EU environmental transfers received by each farm. The identification strategy relies on the idea that these targeted green funds affect farm outcomes primarily through their impact on the adoption of adaptation technologies, rather than through direct and unrelated productivity channels.

Climate data (E-OBS). We measure local climate conditions using the E-OBS gridded observational dataset provided by the Copernicus Climate Change Service, which reports daily weather variables across Europe at a spatial resolution of $0.1^\circ \times 0.1^\circ$ (approximately 11 km) (Cornes et al., 2018). We use daily mean temperature over the period 2008–2021, corresponding to the time window covered by the farm-level data.²

Following the climate-economics literature, we construct annual measures of temperature exposure that capture nonlinear heat stress relevant for agricultural production (e.g., Caggese et al., 2025). Specifically, for each grid cell and year we compute the number of hot days, defined as days with mean temperature above 30°C , and the number of very hot days, defined as days with mean temperature above 35°C . These measures are obtained by aggregating daily observations within each year. To match climate conditions to farms, we exploit the geographic location of farms at the province level. Climate variables are aggregated at the province-year level and merged with the farm panel according to the farm’s province and year of observation. This approach balances spatial precision with data availability and is commonly used when exact farm coordinates are not observed.

Italy exhibits substantial climatic heterogeneity due to its latitudinal extension, complex topography, and strong regional variation in temperature patterns. Southern regions and inland areas experience substantially higher exposure to extreme heat compared to northern regions,

²The E-OBS dataset is publicly available from the Copernicus Climate Data Store: <https://cds.climate.copernicus.eu>. Province boundaries are obtained from official ISTAT shapefiles. Province centroids are computed using geographic overlays and matched to the nearest E-OBS grid cell.

providing meaningful cross-sectional variation for identifying the impact of temperature shocks on farm outcomes.

Potential yields (GAEZ). For global and cross-sectional analyses, we use potential yield estimates from the Global Agro-Ecological Zones (GAEZ) database produced by FAO and IIASA. GAEZ provides high-resolution predictions of potential yields (tons per hectare) under given agro-climatic conditions, based on agronomic models that incorporate soil, elevation, and climate. We focus on baseline potential yields around the year 2000 (e.g., for wheat as a benchmark crop) and aggregate grid-cell outcomes to provinces or countries when needed following the approach in [Adamopoulos and Restuccia \(2022\)](#). The key advantage of these measures of potential yields provided by GAEZ is that they summarize the heterogeneous impact of land quality and geography into a concrete productivity measure. These measures of potential yield then provide a quantification of climate-induced changes based on climate change scenarios.

Cross-country development and farm structure. To relate farm structure to development, we combine national measures of income from the Penn World Tables (GDP per capita in PPP terms) with historical series from the Maddison Project Database. We use country-level measures of average farm size (hectares), constructed from agricultural census and survey sources (e.g., FAO/WCA), and merge these with the development indicators. These data are used to document stylized facts on how farm size, agricultural employment, and exposure to climate damages vary across the income distribution.

Merging and construction. For Italy, we merge RICA to E-OBS at the province-year level and then estimate farm-level relationships between productivity/adaptation outcomes and temperature exposure. For the global component, we align GAEZ potential yields and climate measures to a common grid and then aggregate to the country level before merging with income and farm-size indicators. Throughout, we ensure consistent spatial and temporal alignment across sources and verify that results are robust to alternative assignment rules (nearest-neighbor vs.

within-area averaging) and alternative climate summaries.

3 Empirical Findings

We document a set of empirical observations that motivate the main mechanisms considered in the model in the next section. We first provide cross-country evidence that global warming is projected to decrease potential yields in agriculture, an effect that differs substantially across countries but that is not systematically related to the level of aggregate labor productivity. We also document that developing compared to advanced countries feature a larger proportion of individuals engaged in agriculture, smaller average farm sizes, and lower adaptation capacity to climate change. We then provide farm-level evidence from Italy that climate shocks affect disproportionately more the productivity of smaller farms as they engage less in adaptation. In particular, the evidence indicates that adaptation intensity is size-dependent: smaller farms invest less in mitigation technologies and therefore experience larger productivity losses from climate shocks. Climate-related productivity losses are steeper at smaller farm sizes, and investment in adaptation attenuates the climate–productivity relationship, consistent with the aggregate cross-country evidence on adaptive capacity.

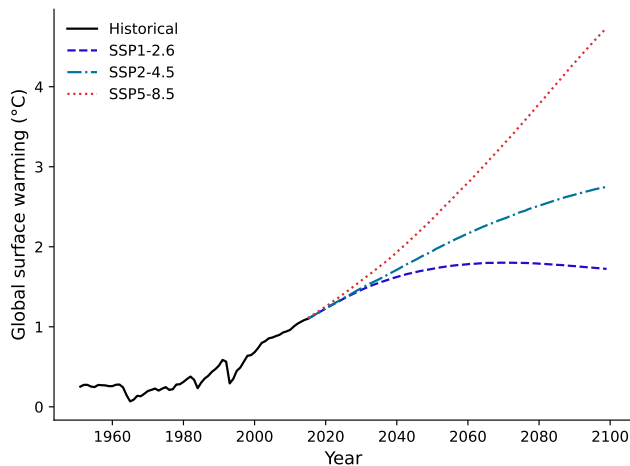
3.1 Cross-Country Evidence

Fact 1: Global warming reduces potential yields. Global temperatures have risen substantially since the pre-industrial period and are projected to increase further over the twenty-first century. Because crop growth is highly sensitive to temperature and water stress, continued warming implies sizable reductions in potential agricultural productivity. We highlight three patterns. First, global mean temperature has increased and continues to rise under alternative emissions trajectories. Second, warming is uneven across space, so the increase in HeatExposure differs sharply across regions. Third, temperature changes translate into large and spatially heterogeneous declines in potential yields of major staple crops.

A large empirical and simulation-based literature finds sizable negative effects of higher temperatures on crop yields. Across meta-analyses and crop-model ensembles, a 1°C increase in growing-season temperature reduces yields of major cereals by roughly 3–7% on average. For example, [Zhao et al. \(2017\)](#) estimate yield declines of -7.4% for maize, -6.0% for wheat, -3.2% for rice, and -3.1% for soybean per 1°C temperature increase.

Figure 1 plots observed global temperature anomalies together with projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) multi-model ensemble. Relative to the 1850–1900 baseline, global mean temperature has already increased by about 1.1°C . Under a low-emissions pathway (SSP1–2.6), warming stabilizes around 2°C by 2100; under a middle pathway (SSP2–4.5), warming reaches roughly 3°C ; and under a high-emissions pathway (SSP5–8.5), warming exceeds 5°C . The key point is that further warming is projected across scenarios, with large differences in magnitude depending on emissions.

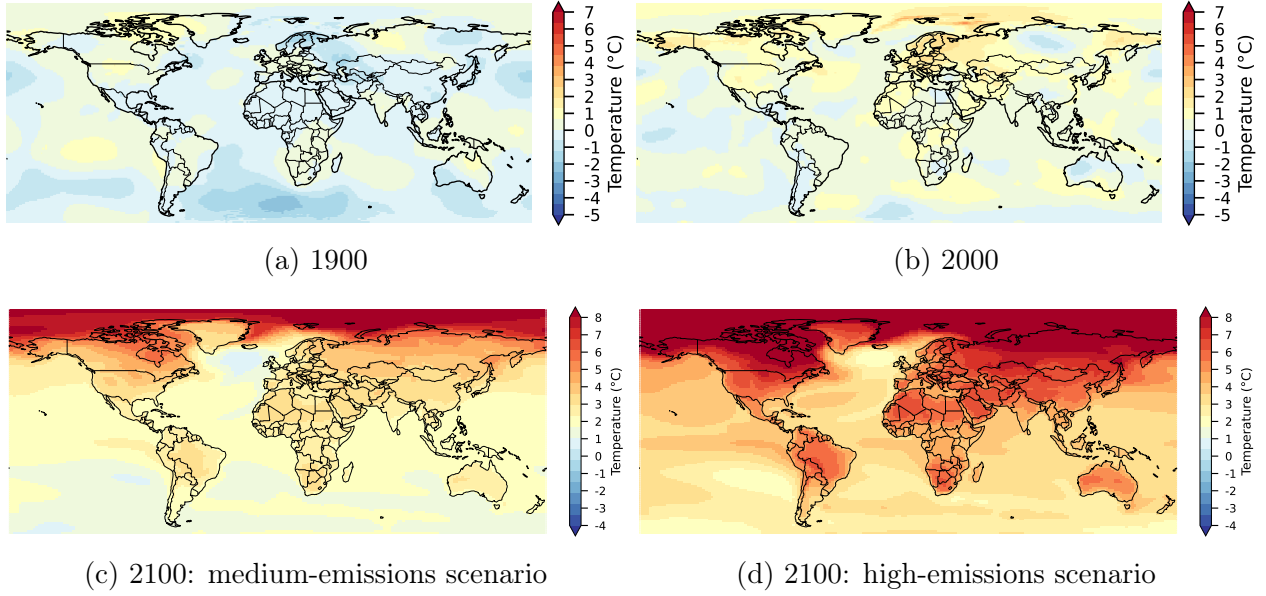
Figure 1: Global Average Temperature Projections



Notes: Temperature anomalies are relative to the 1850–1900 average from Coupled Model Intercomparison Project Phase 6 (CMIP6). Data are from [Fyfe et al. \(2022\)](#). The solid black line shows historical observations. The dashed blue, dash-dotted navy, and dotted red lines show projections under SSP1–2.6, SSP2–4.5, and SSP5–8.5, respectively.

Figure 2 shows that the rise in temperature is not uniform across space. Some regions experience substantially larger increases in HeatExposure than others, reflecting both geography and baseline climate conditions. These spatial differences matter for agriculture because yield responses are highly nonlinear: damages rise sharply when temperatures move beyond crop-

Figure 2: Temperature Anomaly ($^{\circ}\text{C}$)

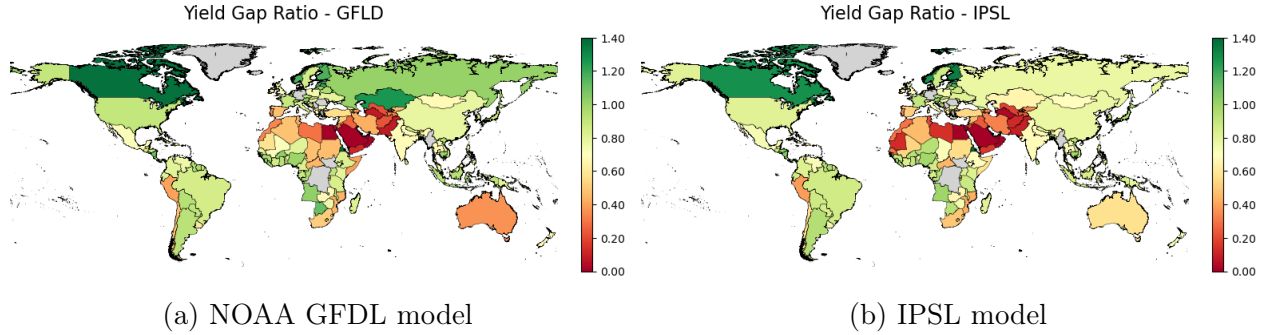


Notes: Temperature anomalies are relative to the 1850–1900 average. Data are from [Rohde and Hausfather \(2020\)](#). Panels show historical anomalies (1900, 2000) and projected anomalies for 2100 under medium- and high-emissions scenarios.

specific thresholds. The unequal pattern of warming therefore implies unequal pressure on attainable productivity across regions.

Figure 3 summarizes projected changes in potential yields for the 2050s (period 2041–2070) from GAEZ v4.0 (GAEZv4.0, 2021) based on the latest climate change projections of the Intergovernmental Panel of Climate Change (IPCC) in its fifth Assessment Report (AR5), and for two climate models, GFLD-ESM2M and IPSL-CM5A-LR, with CO_2 fertilization and with only rainfed water supply. See [Adamopoulos \(2025\)](#) for details of the construction of potential yields for these climate scenarios. For each country, we construct a crop-share-weighted average potential yield across major staples, and plot the ratio of future to current potential yields. Current potential yields use GAEZ’s baseline climate conditions over 1960–1990, that iron out idiosyncratic year-to-year weather variation. This allows us to compare recent long-run trends to future long-run trends. Values below one indicate projected declines in attainable yields under otherwise favorable production conditions. The projections imply large and uneven losses. Yield declines are concentrated in low-latitude, already warm regions, while some high-latitude

Figure 3: Projected Change in Potential Yields under a Moderate-Emissions Scenario



Notes: Data are from the Global Agro-Ecological Zones (GAEZ) v4 database. The figure reports the ratio of projected to current potential yields for each country, where potential yields are computed under high-input and rainfed-water-availability assumptions. Projections compare 2041-2070 under a high-emissions scenario to GAEZ's baseline 1960-1990 climate conditions. Country-level outcomes are constructed as crop-share-weighted averages across major staple crops, using baseline crop shares. The two panels use climate projections from the NOAA *Geophysical Fluid Dynamics Laboratory* (GFDL) model and the *Institut Pierre-Simon Laplace* (IPSL) model. Values below one indicate yield losses relative to current potential yields.

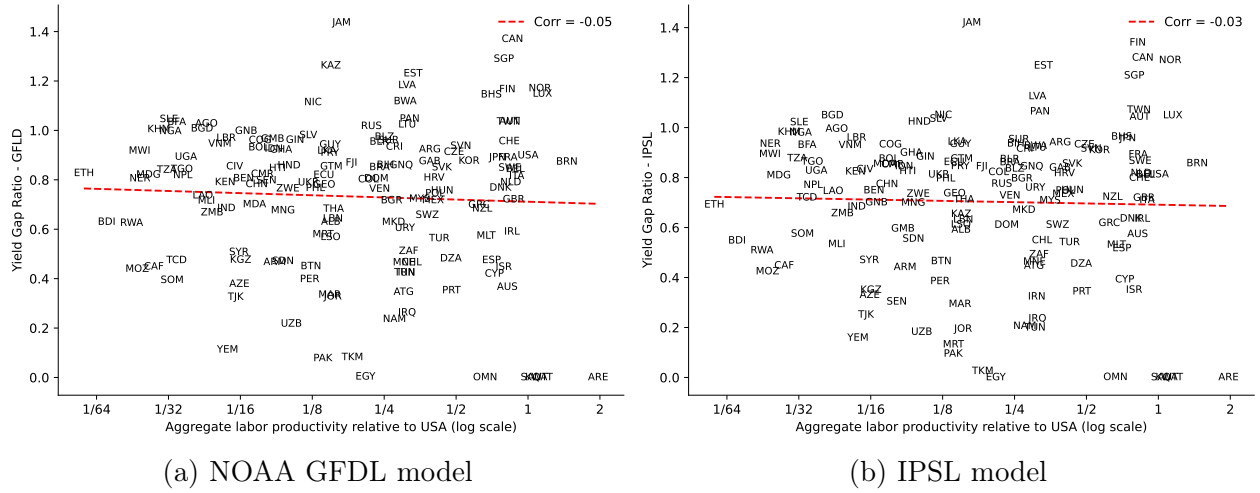
regions exhibit modest gains.

Figure 4 plots the ratio of projected potential yields in the 2050s (2041–2070) relative to current potential yields (using GAEZ's baseline 1960-1990 climatic conditions) against labor productivity relative to Italy. Across both climate models (NOAA GFDL and IPSL), the figure shows no strong systematic relationship between projected potential-yield changes and aggregate labor productivity. In other words, climate-driven yield impacts are not concentrated only among poorer or richer countries when viewed through the cross-country development gradient.

Nevertheless, Figure 4 indicates substantial average losses and large dispersion in predicted loss within productivity groups. On average, countries face projected potential-yield declines of about 30% (ratios around 0.7), but this average effect masks pronounced heterogeneity among countries with similar productivity levels. In particular, many countries experience much larger projected losses, with potential yields declining by 70%–90% in the most affected cases.

Fact 2: Developing countries depend more on agriculture featuring smaller farm sizes. A second set of facts show how agricultural share varies with income. In poorer countries, a much larger share of the labor force works in agriculture, and the sector accounts

Figure 4: Projected Potential Yields, 2041–2070 relative to current



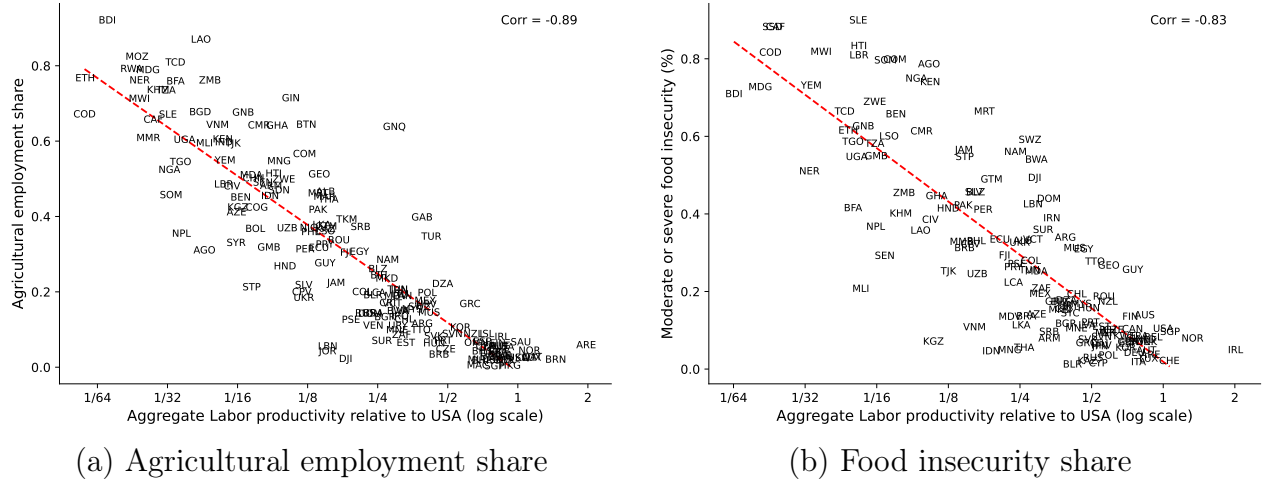
Notes: Data are from the Global Agro-Ecological Zones (GAEZ) v4 database. The figure reports the ratio of projected to current potential yields for each country, where future potential yields are computed under high-input and rainfed-water-availability assumptions. Projections compare 2041-2070 under a high-emissions scenario to GAEZ’s baseline 1960-1990 climate conditions. Country-level outcomes are constructed as crop-share-weighted averages across major staple crops, using baseline crop shares. The two panels use climate projections from the NOAA *Geophysical Fluid Dynamics Laboratory* (GFDL) model and the *Institut Pierre-Simon Laplace* (IPSL) model. Values below one indicate yield losses relative to current potential yields.

for a larger fraction of aggregate production. As countries develop, labor reallocates out of agriculture toward more productive sectors (Gollin et al., 2002; Restuccia et al., 2008; Gollin et al., 2014). Figure 5(a) illustrates this pattern: agricultural employment shares are high in low-income economies and decline sharply with GDP per capita. This matters for climate vulnerability because a given fall in agricultural productivity mechanically has a larger aggregate impact when agriculture employs a larger share of workers and production.

In addition, food insecurity is far more prevalent in low-income economies as documented in Figure 5(b). The fraction of the population facing moderate or severe food insecurity is close to zero in most high-income countries but remains large in many poorer countries. This pattern indicates that a larger share of households is close to subsistence levels of food consumption, so climate-driven productivity declines are more likely to generate meaningful welfare losses through heightened food insecurity.

A closely related fact is that farming is much more small-scale in poorer countries. Average

Figure 5: Agricultural Employment Share and Food Insecurity

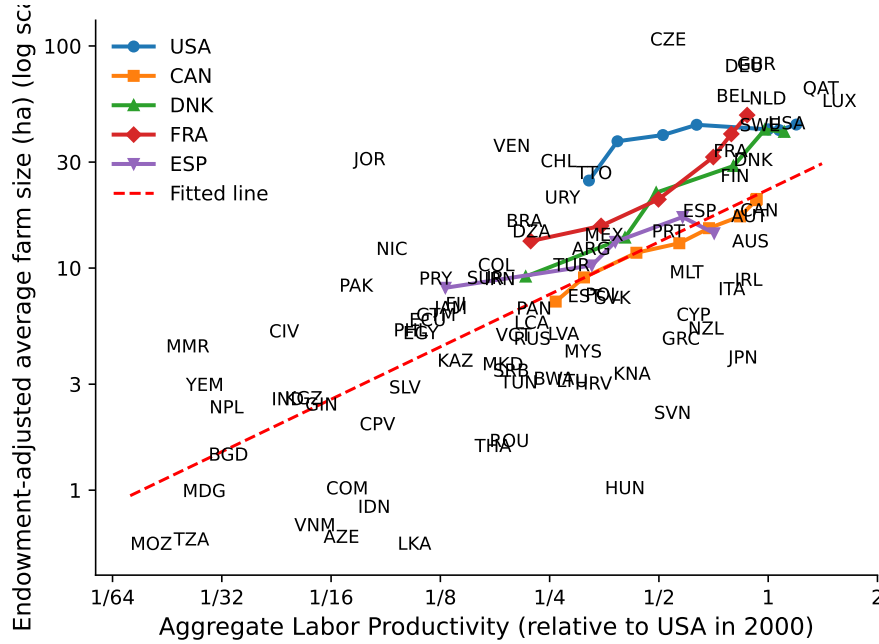


Notes: Country codes denote country observations. Agricultural employment shares are from International Labour Organization (ILO) Statistics. Food insecurity is the share of the population facing moderate or severe food insecurity (percent), from FAOSTAT. Aggregate labor productivity data are from the Penn World Table (Feenstra et al., 2015) both for the year 2000.

farm size is strongly increasing in income (Figure 6). Panel (a) plots average farm size against GDP per capita and shows a steep positive relationship. Panel (b) adjusts farm size for cross-country differences in agricultural land endowments; the relationship remains, indicating that land availability alone does not account for the pattern. Following Adamopoulos and Restuccia (2014), this points to frictions—including land-market distortions, tenure systems, and constraints on capital deepening—that limit consolidation and prevent scale from rising in poorer economies. This scale gap is central for our mechanism because many mitigation technologies involve fixed costs and complementary investments, so technology investment incentives are likely to differ by scale.

Taken together, these cross-country facts imply that poorer countries are more exposed to climate risk: agriculture is larger, farms are smaller, and more households operate close to subsistence. The next section turns to micro evidence on whether small farm size is associated with lower adaptation and larger heat-related productivity losses, and whether adaptation can mitigate these losses.

Figure 6: Average Farm Size (endowment-adjusted) across Countries and over Time

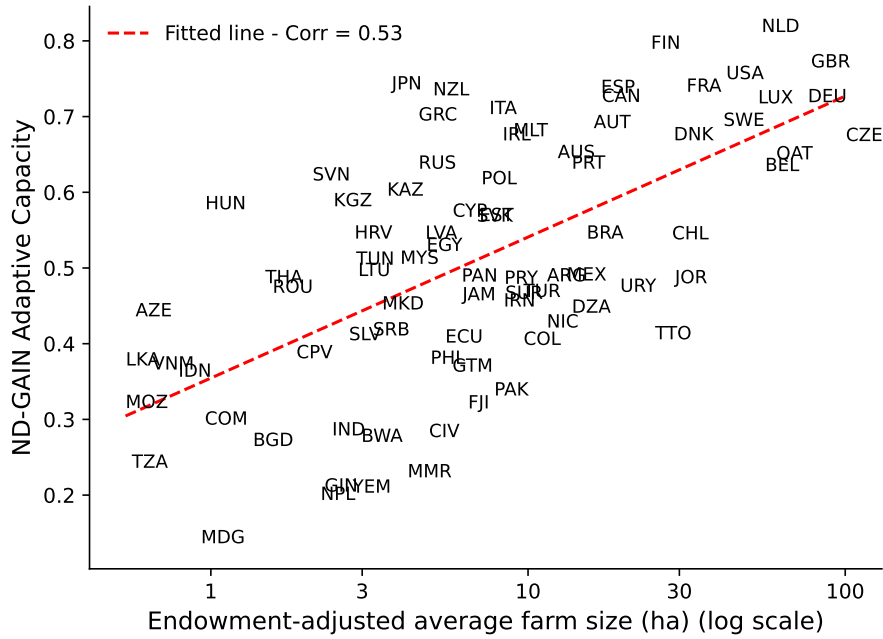


Notes: Country codes denote each country observation. Farm size is measured in hectares (log scale) from FAOSTAT. Average farm size is adjusted for differences in agricultural land endowment, that is average farm size divided by the ratio of land per capita in the country to that of the United States. Aggregate labor productivity data are from the Penn World Table (Feenstra et al., 2015) for the year 2000. Historical time series for individual countries from Maddison Historical Statistics.

Fact 3: Countries with higher average farm size exhibit stronger climate adaption capacity. We combine measures of average farm size with a country-level index of adaptive capacity from the Notre Dame Global Adaptation Initiative (ND-GAIN) dataset. The ND-GAIN adaptive capacity index summarizes a country’s readiness and ability to cope with climate risks through economic, institutional, and infrastructural conditions. In the data, countries with larger farms exhibit systematically higher adaptive capacity.

Figure 7 plots the ND-GAIN adaptive capacity index against average farm size. The relationship is positive and strong: countries with small farms tend to score low on adaptive capacity, while countries with large farms tend to score high. This correlation is robust to adjusting farm size for differences in agricultural land endowment. Figure ?? repeats the exercise using “endowment-adjusted” farm size, constructed by scaling each country’s average farm size to the counterfactual level it would have if the country had the same agricultural land per capita as

Figure 7: Adaptive Capacity and Average Farm Size across Countries



Notes: ND-GAIN adaptive capacity index against endowment-adjusted farm size measure that scales each country's average farm size by the ratio of its agricultural land per capita to that of the United States, so that the horizontal axis reflects the implied farm size controlling for differences in agricultural land per capita. The adaptive capacity index is from the ND-GAIN Country Index; average farm size and agricultural land per capita are from FAOSTAT.

the United States. The positive association remains, suggesting that the farm size gradient in adaptive capacity does not simply reflect land abundance.

The cross-country data provides further evidence suggesting that small farm tend to have weaker adaptive capacity, consistent with a lower propensity to adopt mitigation technologies and a higher vulnerability to climate shocks.

3.2 Farm-Level Evidence

Fact 4: Climate change affects smaller farms more because they invest less in adaptation technology. In order to observe the farm-level evidence on how climate change interacts with farm size and adaptation technology use we use the microdata from the Italian farm panel (RICA) and document three patterns. First, climate change, approximated by different measures of changes in temperature that we call HeatExposure, reduce farm-level

productivity and the productivity losses are larger for smaller farms. Second, investment of adaptation technologies is increasing in farm size so that smaller farms use adaptation technologies less. Third, adaptation attenuates the negative productivity impact of HeatExposures, with causal evidence from an instrumental-variable strategy.

Farm-level productivity effects of climate change and farm size. We begin by estimating how climate (HeatExposures) affects farm productivity and whether the effect depends on farm size. We specify the following empirical equation:

$$\begin{aligned} \log(\text{TFP}_{it}) = & \beta_0 \log(\text{FarmSize}_{i0}) + \beta_1 \text{HeatExposure}_{it} \\ & + \beta_2 (\log(\text{FarmSize}_{i0}) \times \text{HeatExposure}_{it}) + \gamma_{t \times s} + \gamma_{t \times a} + \varepsilon_{it} \end{aligned} \quad (1)$$

where $\log(\text{TFP}_{it})$ denotes farm-level total factor productivity and FarmSize_{i0} is the initial farm size, measured as cultivated land at the beginning of the panel. To account for potential nonlinearities in the impact of heat exposure on productivity and to capture both the intensity and variation of temperature shocks, we consider alternative measures that separately identify extreme heat, moderate heat, and interannual temperature changes. HeatExposure_{it} captures extreme HeatExposure and is alternatively measured as the number of days with temperature above 35°C, the number of days with temperature between 30°C and 35°C, or the annual temperature anomaly. The specification includes year-by-farm type and year-by-altitude fixed effects, which control for time-varying shocks common to farms operating in the same sector and altitude group. Identification therefore relies on variation in local weather exposure over time, while initial farm size is predetermined with respect to contemporaneous weather realizations. The results are reported in Table 2, where each column corresponds to a different measure of HeatExposure.

In order to ensure the robustness of our estimations, we conduct two sets of robustness exercises to assess the stability of our findings with respect to both functional form and the measurement of heat exposure. First, Fig.B.1.1 we estimate quantile regressions to examine

Table 2: HeatExposures, Farm Size, and Farm TFP

<i>HeatExposure measure:</i>	Dependent variable: $\log(\text{TFP}_{it})$		
	(1)	(2)	(3)
	# Days > 35°C	# Days 30–35°C	ΔTemp
$\log(\text{FarmSize}_{i0})$	0.122*** (0.020)	0.095*** (0.030)	0.131*** (0.018)
HeatExposure_{it}	−0.024*** (0.009)	−0.005* (0.003)	−0.050** (0.022)
$\log(\text{FarmSize}_{i0}) \times \text{HeatExposure}_{it}$	0.008*** (0.003)	0.002* (0.001)	0.008** (0.004)
Constant	−0.315*** (0.077)	−0.218* (0.130)	−0.346*** (0.067)
Observations	98,098	98,098	69,718
Year $\times$ farm type FE	✓	✓	✓
Year $\times$ altitude FE	✓	✓	✓

Notes: The unit of analysis is a farm–year. The dependent variable is farm-level TFP, $\log(\text{TFP}_{it})$. The sample includes crop-producing farms only. Columns (1)–(3) estimate equation (1) using alternative measures of HeatExposure: the number of very hot days (> 35°C), the number of hot days (30–35°C), and the change in temperature (ΔT). All specifications include year-by-farm type and year-by-altitude fixed effects. Farm type refers to the farm’s main production specialization (e.g., cereals, horticulture, Permanent crops), while altitude identifies the geographical location of the farm and is classified into three categories: plains, hills, and mountainous areas. Standard errors are clustered at the provincial level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

how the relationship between farm size, heat exposure, and productivity varies along the conditional distribution of TFP. In this specification, heat exposure is proxied by the number of days with temperatures above 35°C (the same patterns is observable for Days between 30° and 35°). This approach allows the coefficients to differ across productivity levels, rather than being constrained to capture an average effect. The results reveal a clear and systematic pattern. The coefficient on farm size is negative at the lower end of the productivity distribution and becomes positive, and increasing, at higher quantiles, indicating that size is only associated with higher productivity among more productive farms. At the same time, the interaction between farm size and heat exposure is positive at all quantiles and increases monotonically. This implies that larger farms are consistently less affected by extreme heat, with the mitigating effect of size becoming stronger among high-productivity farms. Overall, these results show that the baseline

findings are not driven by a specific part of the distribution, but reflect a pervasive pattern of heterogeneous responses. Second, we address concerns related to the measurement of heat exposure by adopting the Moscona–Sastry approach, described in the Appendix and reported in Table B.2. This alternative measure captures exposure at the crop–farm–day level, providing a more comprehensive and economically meaningful characterization of heat exposure compared to simple threshold-based measures such as days above 35°C. Re-estimating our specification with this measure yields results that are fully consistent with the baseline. Heat exposure has a negative effect on productivity, while its interaction with farm size remains positive and statistically significant across specifications. The magnitude of the interaction is, if anything, larger, reinforcing the interpretation that larger farms are better able to mitigate the adverse effects of heat exposure. These results hold both when farm size is measured as initial size in specifications without farm fixed effects, and when time-varying farm size is used alongside farm fixed effects, indicating that the mitigating effect of size is not driven by time-invariant unobserved heterogeneity but reflects a within-farm relationship over time. Taken together, these exercises strengthen the credibility of our main result by showing that it is robust both to allowing for heterogeneous effects across the productivity distribution and to using a more refined measure of heat exposure.

Farm size and drip irrigation as adaptation technology. We next assess whether farm size related to the extent of drip irrigation use. We specify the following empirical equation:

$$\begin{aligned} \log(\text{Drip}_{it} + 1) = & \beta_1 \log(\text{FarmSize}_{i0}) + \beta_2 \text{HeatExposure}_{it} \\ & + \beta_3 (\log(\text{FarmSize}_{i0}) \times \text{HeatExposure}_{it}) + \gamma_{t \times s} + \gamma_{t \times a} + u_{it} \end{aligned} \quad (2)$$

where $\log(\text{Drip}_{it} + 1)$ denotes the cultivated area irrigated with drip technology, used as a proxy for the use of adaptation technologies, HeatExposure_{it} is the local temperature anomaly. In this specification we focus on the temperature anomaly as a parsimonious summary measure of HeatExposure ; results are qualitatively similar when HeatExposures are measured using the number of hot days, as in Table 2. The HeatExposure enters the specification to capture the

demand for adaptation induced by weather realizations, while the interaction with baseline farm size allows adaptation responses to differ across farms of different scale. Table 3 reports the estimates. HeatExposures reduce adaptation on average, while the positive interaction term indicates that this negative effect becomes weaker for larger farms and stronger for smaller farms. The baseline results are robust to alternative ways of conditioning on farm heterogeneity. First, we re-estimate the specification excluding the level effect of farm size and retaining only heat exposure and its interaction with initial size (Table B.3). This exercise addresses the concern that the baseline relationship may be driven by the direct correlation between farm size and adoption. By focusing solely on the interaction term, we isolate the differential response to heat exposure across farms of different sizes. The results remain unchanged, indicating that the mitigating role of size is not mechanically driven by its level effect on adoption, but reflects a genuine differential sensitivity to heat exposure. Second, we replace initial farm size with baseline productivity (Table B.5). This specification tests whether the mechanism operates through scale per se or more broadly through underlying farm capacity. Conditioning on initial productivity provides an alternative ranking of farms based on efficiency rather than size, and also mitigates concerns that farm size may proxy for unobserved heterogeneity. The results are qualitatively similar: heat exposure reduces adoption, while the interaction term remains positive, indicating that more productive farms are better able to adjust. Third, we re-estimate the specification using a Poisson pseudo-maximum likelihood estimator (Table B.4), which allows us to model adaptation in levels and naturally accommodates the large mass of zero observations. This provides a robustness check to the log-transformation used in the baseline specification, ensuring that the results are not driven by functional form assumptions or by the treatment of zero outcomes. The findings remain qualitatively unchanged: heat exposure reduces adaptation, while the interaction with farm size remains positive, confirming that larger farms are better able to mitigate the adverse effects of heat exposure. Taken together, these exercises show that the main mechanism is not specific to the choice of initial farm size, but reflects a more general pattern whereby farms with greater initial capacity—whether in terms of scale or productivity—are better able to respond to heat exposure.

Table 3: Farm Size, HeatExposures, and Adaptation (Drip Irrigation)

<i>HeatExposure measure:</i>	Dependent var: $\log(\text{Drip}_{it} + 1)$		
	(1)	(2)	(3)
	Δ Temperature		
$\log(\text{FarmSize}_{i0})$	0.082*** (0.002)	0.076*** (0.003)	0.076*** (0.003)
HeatExposure		-0.032*** (0.053)	-0.052*** (0.009)
$\log(\text{FarmSize}_{i0}) \times \text{HeatExposure}$			0.008** (0.003)
Constant	0.080*** (0.006)	0.098** (0.007)	0.097** (0.007)
Observations	98,175	69,769	69,769
Year $\times$ farm type FE	✓	✓	✓
Year $\times$ altitude FE	✓	✓	✓

Notes: The unit of analysis is a farm–year. The dependent variable is $\log(\text{Drip}_{it} + 1)$. “HeatExposure” is measured as the change in average temperature relative to the previous year in the same location. All specifications include year-by-farm type and year-by-altitude fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Adaptation mitigates farm productivity losses. We assess whether adaptation flattens the climate–productivity relationship across farms. We specify the following empirical equation:

$$\begin{aligned} \Delta \log(\text{TFP}_{it}) = & \delta_0 \log(\text{Drip}_{it} + 1) + \delta_1 \text{HeatExposure}_{it} \\ & + \delta_2 (\text{HeatExposure}_{it} \times \log(\text{Drip}_{it} + 1)) + \gamma_{t \times s} + \gamma_{t \times a} + \eta_{it} \end{aligned} \quad (3)$$

where $\log(\text{Drip}_{it} + 1)$ denotes the cultivated area equipped with drip irrigation technologies. While drip irrigation may be adopted for several reasons, it represents an important margin of adjustment that can help farms cope with heat stress. HeatExposure_{it} is the temperature anomaly defined above. The coefficient of interest is δ_2 : a positive value implies that farms with greater drip irrigation experience smaller productivity losses when HeatExposures increase.

Because drip irrigation may be endogenous, we instrument $\log(\text{Drip}_{it} + 1)$ and its interaction with HeatExposure_{it} using the log of EU environmental and agro-climatic investment funds

received by the farm and the interaction of these funds with HeatExposure_{it} . Table 4 reports both OLS and 2SLS estimates. We also estimate a dynamic specification in which adaptation is lagged and the dependent variable is the change in TFP growth, providing a robustness check against reverse causality. The first-stage results indicate strong instruments, and the 2SLS estimates show that drip irrigation significantly attenuates the productivity impact of HeatExposures among farms whose investment decisions respond to these funding opportunities.

Table 4: HeatExposures, Adaptation, and Farm Productivity

	Dependent variable: $\Delta \log(\text{TFP}_{it})$			
	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
$\log(1 + \text{Drip}_{it})$	0.013*** (0.004)	0.005 (0.009)	0.050** (0.018)	0.065* (0.035)
$\text{HeatExposure}_{it} \times \log(1 + \text{Drip}_{it})$	0.015 (0.009)	0.014 (0.027)	0.110** (0.055)	0.183** (0.066)
HeatExposure_{it}	-0.041* (0.025)	-0.033 (0.06)	-0.174** (0.086)	-0.255** (0.121)
Observations	3,057	2,742	3,057	2,742
Year $\times$ farm type FE	✓	✓	✓	✓
Year $\times$ altitude FE	✓	✓	✓	✓
Kleibergen-Paap F			18.785	18.599

Notes: The unit of analysis is a farm-year. The dependent variable is farm-level TFP growth, $\Delta \log(\text{TFP}_{it})$. HeatExposure_{it} is delta temperature defined above in Table 3. The endogenous regressors are $\log(\text{Drip}_{it})$ and $\text{HeatExposure}_{it} \times \log(\text{Drip}_{it})$, instrumented using the log of EU environmental and agro-climatic funds received by the farm and its interaction with HeatExposure_{it} . Column (3) estimates this specification using contemporaneous adoption. Column (4) uses lagged drip and the dependent variable is growth in TFP. Standard errors are clustered at the province level.

The 2SLS coefficient on the interaction term is positive and statistically significant, indicating that adaptation mitigates the productivity impact of HeatExposures. Interpreting the interaction in (3), a 1% increase in adaptation intensity reduces the marginal TFP loss from a 1°C increase in the temperature anomaly by roughly 0.10–0.13 percentage points in our baseline specifications.

4 Model

We develop a model of structural transformation between agriculture and non-agriculture, building on [Gollin et al. \(2002\)](#) and [Restuccia et al. \(2008\)](#). The model incorporates production heterogeneity in agriculture as in [Adamopoulos and Restuccia \(2014\)](#) and introduces productivity losses from climate change. Farmers choose whether to invest in climate adaptation technologies. We examine how technological and institutional factors that shape the farm size distribution influence climate adaptation decisions and their macroeconomic consequences for structural transformation and productivity.

4.1 Economic Environment

Technologies. At each date two goods (agriculture and non-agriculture) are produced in sectors. A homogeneous agricultural good is produced by farms indexed by i , with a decreasing returns to scale production function given by

$$y_i = A\kappa(s_{ai}z)^{1-\gamma}\ell_i^\gamma, \quad \gamma \in (0, 1),$$

where y_i denotes agricultural output, ℓ_i is land input, A represents economy-wide productivity, κ is agriculture-specific productivity, and $(s_{ai}z)^{1-\gamma}$ captures the farm's idiosyncratic productivity which has two components. The component s_{ai} reflects farmer's idiosyncratic ability which is drawn from an known and exogenous distribution. The component z reflects idiosyncratic productivity determined by an exogenous climate shock D and the farmer's endogenous investment choices in productivity-enhancing and climate adaptation technology x , which we describe in detail below.

The homogeneous non-agricultural good is produced by a representative firm using efficiency units of labor according to the following constant returns to scale production function:

$$Y_n = AH_n, \tag{4}$$

where A is economy-wide productivity and H_n is aggregate effective labor in non-agriculture. Workers in non-agriculture draw their non-agricultural ability s_{ni} after occupational choices are made from an iid cumulative distribution function $F_n(s_n)$ with $\mathbb{E}[s_{ni}] = 1$. Hence, $H_n = \mathbb{E}[s_{ni}]N_n = N_n$, where N_n is labor in non-agriculture.

Market structure. We assume competitive markets in both sectors and normalize the price of agriculture to one (numeraire). We denote by p_n the relative price of non-agriculture, q the rental rate of land, and w the wage rate per unit of effective labor in non-agriculture.

Preferences and endowments. The economy is populated by a unit mass of individuals. Each individual owns a fixed equal share of the aggregate land stock. Total land supply is exogenous and fixed at L , and is supplied inelastically to farms for agricultural production.

Individuals are ex-ante identical and have Price-Independent Generalized Linear (PIGL) preferences over agricultural and non-agricultural consumption ([Boppart, 2014](#)). Indirect utility as a function of the non-agricultural price p_n and income E is

$$v(p_n, E) = \frac{1}{1-\varphi} E^{1-\varphi} - \frac{\alpha}{1-\rho} p_n^{1-\rho} - \frac{1}{1-\varphi} + \frac{\alpha}{1-\rho},$$

where α is the preference weight on agricultural consumption, φ is the income elasticity, and ρ is the price elasticity.

The implied Hicksian demand for the agricultural good c_a is given by

$$c_a = \alpha E^\varphi p_n^{\sigma-\varphi}, \quad \text{if } c_a < E,$$

and $c_a = E$ otherwise. The demand for the non-agricultural good c_n is solved from the budget constraint $p_n c_n + c_a = E$, given E , p_n , and the solution for c_a .

Occupational choice. Following [Adamopoulos and Restuccia \(2014\)](#), we abstract from occupational selection by assuming that all individuals are ex-ante identical and only observe

their sector ability after choosing an occupation. Selection has been studied extensively in the literature (Lagakos and Waugh, 2013; Adamopoulos et al., 2022) and we focus instead on the farm size distribution and heterogeneity *within* sectors. Because labor is perfectly mobile across sectors and only realize their sector ability after choosing an occupation, in equilibrium, the expected value of operating a farm equals the expected wage income when working in the non-agricultural sector, so that individuals are indifferent between operating a farm or working in non-agriculture.

Formally, with $V(s_a)$ denoting the value from operating a farm with ability s_a and w the non-agricultural wage per unit of effective labor, an interior occupational allocation requires

$$\mathbb{E}_{s_a}[V(s_a)] = \mathbb{E}_{s_n}[ws_n] = w\mathbb{E}_{s_n}[s_n] = w. \quad (5)$$

After choosing to operate a farm, individuals farm ability is drawn from an iid exogenous distribution $s_{ai} \sim F_a(s_a)$. Realized income for a farmer is given by the farm value $V(s_{ai})$, while an individual working in non-agriculture earns ws_{ni} . In addition, all individuals receive their share of aggregate land rents qL , so that individual income is the sum of sectoral income (farm profit or earnings) and land income.

4.2 Equilibrium

The model is static and we consider a competitive equilibrium in which households, farms, and firms take prices as given, and prices clear the markets.

Incumbent farms. An incumbent farm i is characterized by idiosyncratic productivity s_{ai} and its choice of technology z . The farm's expected per-period profit is given by

$$\pi(s_{ai}z) = \max_{\ell \geq 0} A\kappa(s_{ai}z)^{1-\gamma}\ell^\gamma - q\ell.$$

The optimal land choice and output of an incumbent farm is given by

$$\begin{aligned}\ell(s_{ai}z) &= \left(\frac{\gamma}{q}\right)^{\frac{1}{1-\gamma}} (A\kappa)^{\frac{1}{1-\gamma}} s_{ai}z, \\ y(s_{ai}z) &= \left(\frac{\gamma}{q}\right)^{\frac{\gamma}{1-\gamma}} (A\kappa)^{\frac{1}{1-\gamma}} s_{ai}z.\end{aligned}$$

The optimal expected profit of an incumbent farm is given by

$$\pi(s_{ai}z) = (1 - \gamma) \left(\frac{\gamma}{q}\right)^{\frac{\gamma}{1-\gamma}} (A\kappa)^{\frac{1}{1-\gamma}} s_{ai}z.$$

Climate damage and farm technology. Each farm i is subject to an exogenous and common climate damage shock $D \geq 0$ that in isolation lowers agricultural productivity. We capture climate damage and farm technology by specifying farm technology $z_i \in (0, \infty)$ as a function of the extent of climate damage D and farm investment in productivity-enhancing and adaptation technology (e.g. irrigation, heat-tolerant varieties, soil conservation) $x_i \geq 0$,

$$z_i = g(D, x_i),$$

where the function $g : \mathbb{R}_+^2 \rightarrow (0, \infty)$ satisfies

$$g_D(D, x) < 0, \quad g_x(D, x) > 0, \quad g_{xx}(D, x) \leq 0,$$

implying that climate damage reduces productivity and farm investment raises productivity with diminishing marginal returns.

For the quantitative analysis we parameterize farm technology as

$$z(D, x) = e^{-D} (1 + x)^{\eta_0 + \eta_1 D}, \quad \eta_0 \geq 0, \eta_1 \geq 0. \quad (6)$$

Note that when $D = 0$, η_0 controls the return to farm productivity-enhancing investment

technology independent of climate.

We emphasize that the above specification (in logs) maps into the empirical regression discussed earlier:

$$\log z(D, x) = -D + (\eta_0 + \eta_1 D) \log(1 + x). \quad (7)$$

In the absence of farm investment ($x = 0$), $z(D, 0) = e^{-D}$, D captures the pure climate damage component to farm productivity. The parameter η_0 governs the return to productivity-enhancing investment independent of climate, while η_1 controls the return to adaptation investment to the level of climate damage. When $\eta_0 > 0$, farm investment raises productivity even in the absence of damage ($D = 0$) and $\eta_1 > 0$, adaptation becomes more effective in mitigating damage as D increases. The magnitude of these elasticity parameters determine the extent to which farm investment is productivity-enhancing and adaptation.

We assume a convex cost function of farm investment $k : \mathbb{R}_+ \rightarrow \mathbb{R}_+$,

$$k(x) = \frac{\psi}{1 + \nu} x^{1+\nu}, \quad \psi > 0, \nu \geq 0, \quad (8)$$

where ψ is a scale parameter and ν controls the curvature.

Given the profit function $\pi(s_a z) = \Omega s_a z$ derived above, an incumbent farm with productivity s_a facing damage D chooses farm investment x to solve

$$\Pi(s_a, D, x) = \Omega s_a z(D, x) - k(x) = \Omega s_a e^{-D} (1 + x)^{\eta_0 + \eta_1 D} - \frac{\psi}{1 + \nu} x^{1+\nu}. \quad (9)$$

The first-order condition for an interior solution $x > 0$ is

$$\frac{\partial \Pi}{\partial x} = \Omega s_a e^{-D} (\eta_0 + \eta_1 D) (1 + x)^{\eta_0 + \eta_1 D - 1} - \psi x^\nu = 0. \quad (10)$$

Because equation (10) is nonlinear in x and involves both $(1 + x)$ and x raised to powers, it does not admit a simple closed-form solution for $x^*(s_a, D)$. In the quantitative analysis we therefore

solve equation (10) numerically for $x^*(s_a, D)$, imposing the Kuhn–Tucker conditions $x \geq 0$ and complementary slackness, and then set

$$z(s_a, D) \equiv z(D, x^*(s_a, D)), \quad V(s_a, D) = \Omega s_a z(s_a, D) - k(x^*(s_a, D)).$$

Definition of equilibrium. A *competitive equilibrium* with climate damages D comprises a set of prices (p_n, w, q) , farm-level decision rules for land demand $\ell(s_a, D)$, productivity investment $x(s_a, D)$, climate-adjusted productivity $z(s_a, D)$, output $y(s_a, D)$, profit $\pi(s_a, D)$, and farm value $V(s_a, D)$; agricultural labor allocation N_a ; and individual consumption allocations for farmers $\{c_a^F(s_a), c_n^F(s_a)\}$ and non-agricultural workers $(c_a^W(s_n), c_n^W(s_n))$ such that:

- (i) **Farm problem.** Given prices (q, w, p_n) , policy functions $x(s_a, D)$ and $\ell(s_a, D)$ solve the incumbent farm with ability s_a facing climate damage D , yielding the optimal per-period profit $\pi(s_a, D)$ and value net of adaptation cost $V(s_a, D)$.
- (ii) **Occupational choice.** An interior agricultural employment share $N_a \in (0, 1)$ requires that the expected value of operating a farm equals the non-agricultural wage:

$$\mathbb{E}_{s_a}[V(s_a, D)] = w. \tag{11}$$

- (iii) **Non-agricultural firm problem.** Given prices (p_n, w) , the representative non-agricultural firm's profit maximization problem implies $p_n = w/A$ and the firm is indifferent on the level of labor demand.
- (iv) **Consumption allocations.** Given farm income $I^F(s_a)$ and the relative price p_n , the pair $(c_a^F(s_a), c_n^F(s_a))$ solves the consumption problem of a farm operator with ability s_a . Given prices (w, p_n) and non-agricultural ability s_n , the pair $(c_a^W(s_n), c_n^W(s_n))$ solves the non-agricultural worker's consumption problem.

(v) **Markets clear.** For labor, the agricultural and non-agricultural goods, and land:

$$\begin{aligned} N_a \int_{s_a} c_a^F(s_a) dF(s_a) + N_n \int_{s_n} c_a(s_n)^W dF_n(s_n) + N_a \int_{s_a} k(x(s_a, D)) dF_a(s_a) \\ = Y_a = N_a \int_{s_a} y(s_a, D) dF_a(s_a), \end{aligned}$$

$$N_a + N_n = 1,$$

$$N_a \int_{s_a} c_n^F(s_a) dF_a(s_a) + N_n \int_{s_n} c_n^W(s_n) dF_n(s_n) = Y_n = AN_n,$$

$$N_a \int_{s_a} \ell(s_a, D) dF_a(s_a) = L.$$

5 Quantitative Analysis

We calibrate a benchmark economy to match data moments for Italy. We then perform a series of quantitative experiments to assess the role of factors that shape the farm size distribution on climate adaptation decisions and their macroeconomic consequences.

5.1 Calibration

We calibrate a benchmark economy to micro, sectoral, and aggregate data for the Italy. We proceed in two steps. First, we calibrate to a benchmark economy with no climate damages $D = 0$. In this step we discipline all the parameters except the four parameters related to investment in productivity enhancing and adaptation technology $(\eta_0, \eta_1, \psi, \nu)$. Second, we assume climate damages $D = 0.1$ and calibrate the remaining four parameters to match the empirical estimates from the Italian microdata.

We assume that farming ability s_a is drawn from a lognormal distribution with normalized mean 0 and standard deviation σ_a . Non-agricultural ability s_n is drawn from the lognormal distribution with $E_{s_n}[s_n] = 1$ and standard deviation σ_n . There are 13 parameters to calibrate: the decreasing returns to scale in agricultural production γ , the dispersion in farming ability

σ_a , the dispersion in non-agricultural ability σ_n , the agricultural consumption weight α , the price elasticity ρ , the income elasticity φ , relative productivity in agriculture κ , economy-wide productivity A , the aggregate land endowment L , and the curvature and level parameters of climate adaptation and investment costs $(\eta_0, \eta_1, \psi, \nu)$.

A set of five parameters are either normalized or disciplined by outside evidence. First, we set the decreasing-returns parameter to $\gamma = 0.54$, consistent with agricultural factor income shares reported by [Valentinyi and Herrendorf \(2008\)](#) and standard in the misallocation literature. We set the price-elasticity parameter to $\rho = 0.40$ and the income-elasticity parameter to $\varphi = 0.70$, following [Hao et al. \(2020\)](#). Aggregate and sector productivity parameters are normalized to one $A = \kappa = 1$.

Step 1: Benchmark economy without climate damages. We calibrate a set of four parameters in the benchmark economy assuming no climate damage ($D = 0$) to data for Italy in 2000. We calibrate σ_a to match moments of the size distribution of farms, the land endowment L to match average farm size in agriculture, the preference parameter α the agricultural employment share of 5%. We set σ_n to match the average Gini index of non-agricultural income in Italy (1990-2020, Bank of Italy, [Depalo and Lattanzio \(2023\)](#)), mapped into lognormal dispersion following [Cowell \(2011\)](#). See Table 5 for a summary of parameter values and targeted moments.

Table 5: Summary of Calibrated Parameters and Moments

Parameter	Description	Value	Target moment	Model	Data
α	Pref. weight for agriculture	0.22	Ag. employment share	5.0%	5.0%
σ_a	Farming ability dispersion	1.98	Farm size distribution	{...}	{...}
σ_n	Non-ag ability dispersion	0.60	Non-ag income dispersion	0.60	0.60
L	Land endowment	0.38	Average farm size (ha)	7.5	7.5

Step 2: Climate damage and adaptation technology parameters. We now calibrate the parameters governing climate damage and productivity investment in adaptation. We

assume a climate damage of $D = 0.1$. We parameterize the climate-adjusted investment as

$$\log z(D, x) = -D + \eta_0 \log(1 + x) + \eta_1 D \log(1 + x), \quad (12)$$

where $D \geq 0$ is a reduced-form damage and $\eta_1 > 0$ captures how strongly adaptation x mitigates damage. Recall that the farming production function implies that farm-level TFP in logs is proportional to $(1 - \gamma) \log z(D, x)$ for a farmer with ability s .

In the empirical implementation, we map damages D to temperature T via a linear index $D(T) = \delta T$ so that

$$\log z(D(T), x) = -\delta T + \eta_0 \log(1 + x) + \delta \eta_1 T \log(1 + x),$$

and the climate effect to log TFP is

$$(1 - \gamma) \log z(D(T), x) = -(1 - \gamma) \delta T + (1 - \gamma) \delta \eta_1 T \log(1 + x). \quad (13)$$

At the micro level, we estimate the reduced-form regression

$$\log \text{TFP}_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 \log(1 + x_{it}) + \beta_3 T_{it} \times \log(1 + x_{it}) + \text{controls} + \varepsilon_{it}, \quad (14)$$

where T_{it} is (demeaned) temperature and x_{it} is the measure of adaptation (e.g. irrigated area).

Comparing equations (13) and (14) with $D(T) = \delta T$ yields the mapping

$$\beta_1 = -(1 - \gamma) \delta, \quad \beta_2 = \eta_0 \quad \beta_3 = (1 - \gamma) \delta \eta_1. \quad (15)$$

Hence, we set

$$\delta = -\frac{\beta_1}{1 - \gamma}, \quad \eta_0 = \beta_2, \quad \eta_1 = -\frac{\beta_3}{\beta_1},$$

so the curvature parameter η_1 is identified by the ratio β_3/β_1 and does not depend on γ .

Our baseline regression estimates $\hat{\beta}_1 = -0.126$, $\hat{\beta}_2 = 0.045$ and $\hat{\beta}_3 = 0.184$ imply

$$\eta_0 = \hat{\beta}_2 = 0.045, \quad \eta_1 = -\frac{\hat{\beta}_3}{\hat{\beta}_1} = \frac{0.126}{0.184} \approx 0.68.$$

Thus the marginal effectiveness of adaptation increases with damage at rate $\eta_1 \approx 0.68$. Note that the productivity-enhancing investment component of technology that is independent of damages has a relatively small elasticity $\eta_0 = 0.045$.

We next calibrate the two remaining parameters of the productivity investment cost, the cost curvature parameter ν and the cost scale parameter ψ . We choose the values of these parameters to match moments from our Italian farm evidence. We assume that the economy features a climate damage shock of $D = 0.1$.

We discipline the curvature parameter ν using the reduced-form estimate γ_1 of technology use (measured by Drip) on baseline farm size in equation (2), controlling for HeatExposures and other variables. We target this moment running the same regression in the model, implying $\nu = 2.42$.

Table 6: Summary Calibration Climate Parameters and Moments

Parameter	Description	Value	Source		
<i>Micro estimates</i>					
η_0	Returns to investment	0.045	IV regression estimate		
η_1	Returns to adaptation	0.68	IV regression estimate		
D	Climate damage (BE)	0.10	Estimated damage		
<i>Calibrated under shock $D = 0.10$</i>			Target	Model	Data
ν	Investment cost curvature	2.42	Technology-size elasticity	0.08	0.08
ψ	Investment cost scale	1.31	Average tech inv level	0.30	0.30

We choose ψ to match the average level of productivity investment observed in the data. Let $\overline{\text{Drip}}$ denote the sample mean of Drip_{it} (our measure of $\log(1 + x_{it})$), and let (s_{ai}, D_{it}) denote the farm-damage pairs used in the second-stage regression. Given (δ, η, ν) , we select ψ to match average measure of drip irrigation use $\left(\frac{1}{N} \sum_{i,t} \log(1 + x(s_{ai}, D_{it}))\right)$. This targets the average intensity of technology use, while the curvature parameter ν is disciplined by the cross-sectional

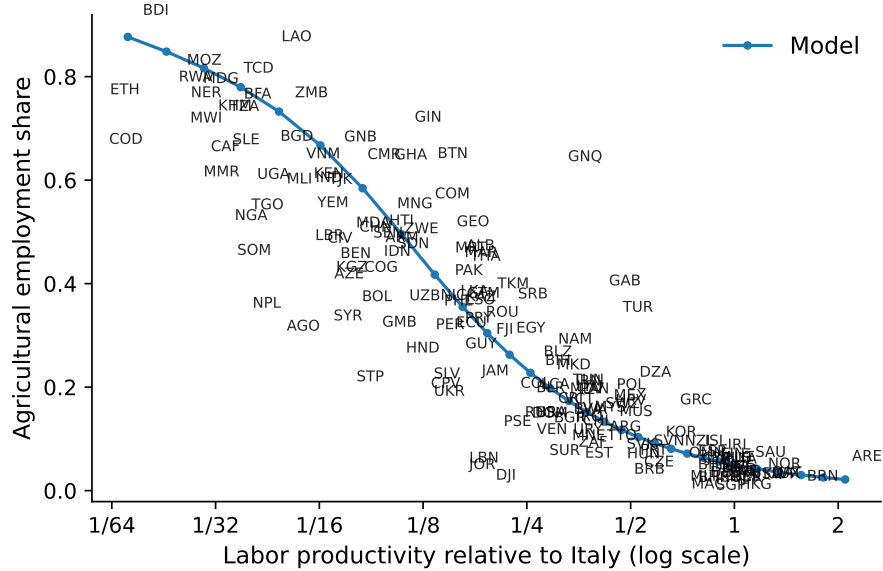
response of technology use to farm size controlling for temperature shocks.

5.2 Cross-Country Experiments

We generate poorer and richer economies relative to the benchmark economy (calibrated to Italy) by varying exogenous economy-wide productivity A and agriculture-specific productivity κ jointly to capture the relationship between aggregate labor productivity and the share of employment in agriculture observed in the data. Specifically, we consider values of (A, κ) ranging from $(0.10, 0.15)$ in the poorest economy to $(1.00, 1.00)$ in the benchmark economy, and to $(2.00, 1.77)$ in the richest economy. We assume that all other parameter values are the same as in the benchmark economy.

Model fit. Figure 8 compares the model and the data for the agricultural employment share plotted against aggregate labor productivity relative to Italy. The model fits the data very well.

Figure 8: Structural Transformation across Countries, Model vs. Data



Notes: The agricultural employment share against labor productivity relative to Italy in 2000. Data on aggregate labor productivity are from PWT 11.0 and data on agricultural employment shares are from the International Labour Organization (ILO).

It is worth noting that the model can generate a wide range of development outcomes. Across the range of productivity values we consider, economies span from aggregate labor productivity

equal to 1/64 of the benchmark to 2 times the benchmark. Over this range, the model generates agricultural employment shares from about 1% to more than 80%. Our range of (A, κ) captures most of the observed development spectrum.

On-impact effects of climate damages. While climate damages on agricultural production are expected to occur over time, we first provide an assessment of their economic impact in our model without any other changes. In our model, this is equivalent to the impact of climate change in an economy with no productivity growth. Later we assess the climate damage impact along with productivity growth. We examine the on-impact effects of climate damages under two permanent agricultural productivity loss scenarios, $D \in \{0.30, 0.70\}$, consistent with the range of potential yield climate scenarios in Figure 4. For each income group (low, middle, and high income), we compare outcomes to the counterfactual of the same economy under no climate damage ($D = 0$), allowing farms to respond through endogenous investment in adaptation technologies.

Table 7 shows that climate damages substantially increases the share of employment in agriculture in low- and middle-income economies, while effects are modest in the high-income benchmark. Under the medium-damage scenario ($D = 0.30$), the share of employment in agriculture rises by 4.6 p.p. in the low-income economy and 7.3 p.p. in the middle-income economy (versus only 0.2 p.p. in the high-income economy). These reallocation effects are accompanied by sizable declines in agricultural productivity: agricultural TFP falls by 18.9% in the low-income economy and 13.8% in the middle-income economy (compared to 4.2% in the high-income economy). As a result, aggregate labor productivity declines by 22.8% in low-income economies and 9.9% in middle-income economies, while remaining essentially unchanged in the frontier economy (-0.4%).

The high-damage scenario ($D = 0.70$) amplifies these patterns. Agricultural employment rises by 8.1 p.p. in the low-income economy and by 19.9 p.p. in the middle-income economy. Agricultural TFP declines reach 36.7% (low-income) and 27.0% (middle-income), translating into

Table 7: Climate Damages On-Impact Effects

	30% climate damage			70% climate damage		
	Low-	Middle-	High-	Low-	Middle-	High-
Share of population (change in p.p):						
Agricultural employment	4.59	7.32	0.24	8.14	19.90	0.61
Agricultural TFP (change in %)	-18.88	-13.80	-4.21	-36.70	-26.95	-10.68
Average productivity losses mitigated by adaptation (%)	<i>8.94</i>	<i>16.80</i>	<i>46.57</i>	<i>7.98</i>	<i>14.49</i>	<i>44.51</i>
Aggregate labor productivity (change in %)	-22.78	-9.91	-0.44	-41.50	-26.42	-1.17
Aggregate labor productivity						
With climate shock D	0.02	0.17	1.00	0.02	0.14	0.99
Baseline with $D = 0$	0.03	0.19	1.00	0.03	0.19	1.00

Notes: Low-income economy has $(A, \kappa) = (0.12, 0.18)$; middle-income has $(A, \kappa) = (0.26, 0.33)$; high-income is the benchmark economy with $(A, \kappa) = (1.00, 1.00)$. All outcomes are computed as changes relative to the same economy under no climate damage ($D = 0$). Aggregate labor productivity is measured using the relative price of non-agriculture of the benchmark economy and normalized by the benchmark economy output at $D = 0$. Agricultural TFP is computed as $Y_a/(N_a^{1-\gamma}L^\gamma)$. Average productivity losses mitigated by adaptation is computed as the percentage of climate loss mitigated by endogenous investment in technology on average across farms.

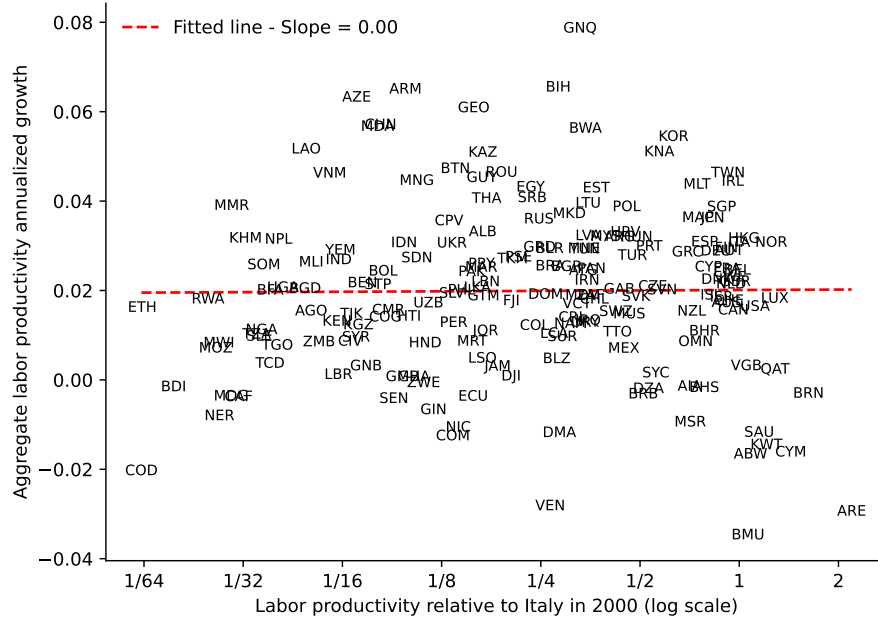
large aggregate labor productivity losses of 41.5% and 26.4%. In contrast, the high-income economy experiences comparatively small aggregate losses (about -1.2%).

A key mechanism behind these heterogeneous impacts is the uneven ability of countries to offset damages through adaptation. Endogenous adaptation mitigates a much larger fraction of productivity losses in the high-income economy (about 45–47%) than in low- and middle-income economies (about 8–17%). Consequently, climate damages widen cross-country productivity gaps: middle-income labor productivity falls from 0.19 to 0.17 under $D = 0.30$ and to 0.14 under $D = 0.70$ (normalized by the high-income benchmark at $D = 0$), while the low-income economy decreases from 3% to around 2% relative to the benchmark economies in both cases.

Projected productivity growth to 2050. We now evaluate climate damages along with productivity growth. We assume a constant annualized growth rate of economy-wide produc-

tivity, g_A , of 2%, together with an additional 1% annual growth rate in agriculture-specific productivity, κ to reflect higher labor productivity growth rate in the agricultural sector, across all economies. These assumptions are motivated by the empirical finding that agricultural productivity growth is typically greater than in non-agriculture (Restuccia et al., 2008; Duarte and Restuccia, 2010). Moreover, as documented in Figure 9, aggregate productivity growth averages around 2% and does not vary systematically with the level of development over the 1990–2018 period. Nevertheless, Figure 9 also reveals wide variation in productivity growth at all levels of development, with some countries growing substantially less than the 2% average and other countries growing substantially more and catching up to the frontier.

Figure 9: Aggregate Labor Productivity Growth across Countries



Notes: Data on aggregate labor productivity are from PWT 11.0. Annualized labor productivity growth rates are estimated by fitting a time trend to log labor productivity over the 1950–2023 period.

Given projected growth in 50 years from the baseline in 2000, we report model outcomes for different economies in 2050. We consider three scenarios: (1) no climate damage, (2) a medium-damage scenario in which climate change reduces agricultural productivity by 30%, and (3) a high-damage scenario in which climate change reduces agricultural productivity by 70%. These scenarios are motivated by our evidence discussed earlier of a wide range of climate effects on potential yields with no systematic differences across countries along the labor productivity

distribution.

Table 8 reports how exogenous growth in A and κ affect labor productivity growth, structural transformation, and food insecurity across economies over a 50-year horizon under the zero climate-loss scenario. Table 8 shows a clear catch-up pattern associated with a common productivity growth of technology scenario across countries: low-income and middle-income economies grow faster than the high-income benchmark in percentage terms, although substantial aggregate productivity gaps remain. In particular, aggregate labor productivity rises by around 7.7-fold from 0.03 to 0.23 in low-income economies, by around 3.4-fold from 0.19 to 0.65 in middle-income economies, and around 2.8-fold from 1.00 to 2.78 in high-income economies. Low-income economies substantially narrow their aggregate labor-productivity gap to the frontier, with relative productivity rising from 3% to 8%, about a 2.7-fold increase. Middle-income economies also reduce the gap, though more gradually, increasing from 19% to 23%, about a 1.2-fold increase.

Table 8: Zero Climate Loss Scenario across Growing Economies

	Low income	Middle income	High income
Aggregate labor productivity:			
2000	0.03	0.19	1.00
2050	0.23	0.65	2.78
<i>2050 relative to high-income</i>	<i>0.08</i>	<i>0.23</i>	<i>1.00</i>
Share of population (change in p.p):			
Agricultural employment	−49.0	−19.5	−2.9

Notes: Low-income economy has $(A, \kappa) = (0.12, 0.18)$; middle-income has $(A, \kappa) = (0.26, 0.33)$; high-income is the benchmark economy with $(A, \kappa) = (1.00, 1.00)$. Outcome variables are computed as changes/growth relative to the case with no growth and no climate damage initially.

The results indicate that aggregate labor productivity catch-up is driven mainly by structural transformation as the exogenous sectoral productivity growth rates are the same across all economies. Low-income economies reallocate labor out of agriculture by 49 percentage points, compared with 19.5 percentage points in middle-income economies and only 2.9 percentage points in high-income economies. This reallocation occurs along with large improvements in

food security: the food-insecure population share declines by 49.6 percentage points in low-income economies and 40.3 percentage points in middle-income economies, while the reduction is modest in high-income economies (1.5 percentage points).

Unequal impact of climate damages across economies. Table 9 reports the effects of climate damage relative to each economy’s no-damage growth path, comparing a 30% and a 70% climate-damage scenario. In both cases, climate damage slows structural transformation out of agriculture, with much larger effects in poorer economies. Under 30% damage, the agricultural employment share is 8.26 percentage points higher than in the no-damage path in low-income economies, compared with 1.05 and 0.06 percentage points in middle- and high-income economies. Under 70% damage, these gaps widen sharply to 22.47, 2.35, and 0.19 percentage points, respectively.

Table 9: Impact of Climate Damages Relative to No-Damage Scenario

	30% climate damage			70% climate damage		
	Low-	Middle-	High-	Low-	Middle-	High-
Share of population (change in p.p):						
Agricultural employment	8.26	1.05	0.06	22.47	2.35	0.19
Agricultural TFP (change in %)	−14.03	−7.52	−2.65	−27.59	−15.43	−8.82
Average productivity losses mitigated by adaptation (%)	<i>17.28</i>	<i>32.52</i>	<i>69.28</i>	<i>14.92</i>	<i>30.33</i>	<i>66.53</i>
Aggregate labor productivity (change in %)	−11.53	−1.38	−0.21	−30.89	−3.05	−0.71
Aggregate labor productivity relative to high-income	0.20 <i>0.07</i>	0.64 <i>0.23</i>	2.78 <i>1.00</i>	0.16 <i>0.06</i>	0.63 <i>0.23</i>	2.76 <i>1.00</i>

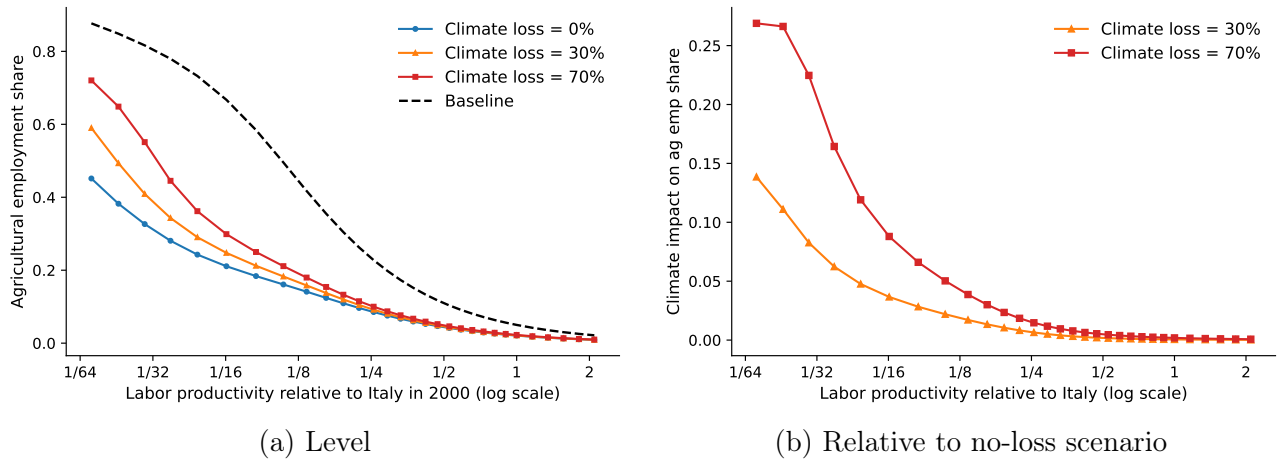
Notes: Low-income economy has $(A, \kappa) = (0.12, 0.18)$; middle-income has $(A, \kappa) = (0.26, 0.33)$; high-income is the benchmark economy with $(A, \kappa) = (1.00, 1.00)$. All outcomes are computed as changes relative to the same economy under no climate damage ($D = 0$). Agricultural TFP is computed as $Y_a/(N_a^{1-\gamma}L^\gamma)$. Average productivity losses mitigated by adaptation is computed as the percentage of climate loss mitigated by endogenous investment in adaptation technology on average across farms.

The structural-transformation results are driven by heterogeneous farm-level adaptation investment responses and thereby different impacts on the agricultural TFP between rich and

poor countries. Climate damage generates much larger declines in agricultural TFP in poorer economies, with agricultural TFP declines by -14% and -27.6% in low-income economies, compared with -7.5% and -15.4% in middle-income economies, and -2.7% and -8.8% in high-income economies. A key reason is unequal adaptation capacity: low-income economies mitigate only 17% and 15% of average farm-level productivity change, while high-income economies mitigate 69% and 66.5%. Because agriculture remains a large sector in poorer economies, these agricultural losses translate into much larger aggregate effects, with aggregate labor productivity decline of -12% and -31% in low-income economies, compared with -1.4% and -3% in middle-income economies and -0.2% and -0.7% in high-income economies.

Projected structural transformation patterns in different climate scenarios. Figure 10 reports how agricultural employment responds across economies under alternative climate-damage scenarios, highlighting both levels and changes relative to no climate damage.

Figure 10: Projected Structural Transformation across Economies



Notes: Panel (a) plots the agricultural employment share against labor productivity relative to Italy in 2000. Panel (b) plots the differences between agricultural employment share in climate damage scenarios vs. the no damage scenario. The x-axis shows the productivity label productivity in 2000.

Figure 10 shows that the model reproduces a strong structural-transformation pattern: technological progress drives labor out of agriculture, but climate damages slow that reallocation even when adaptation is chosen endogenously. Panel 10a shows the agricultural employment share across countries under different climate loss scenarios. In the no-damage scenario, pro-

jected productivity growth generates rapid structural transformation over the 50-year horizon, especially for low-income economies. In particular, low-income economies substantially reallocate labor away from agriculture by about 50 percentage points, with agricultural employment shares falling from roughly 80% to about 30%. Middle-income economies also reallocate labor out of agriculture, with agricultural employment shares declining from around 40% to 20%. High-income economies exhibit limited labor reallocation because their agricultural employment shares are already close to long-run low levels.

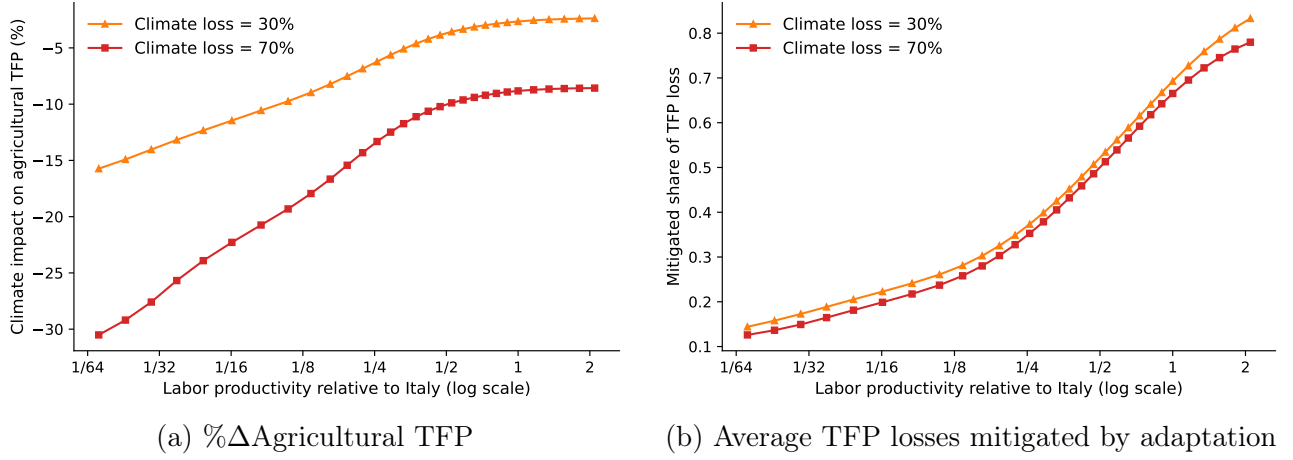
In panel 10b, we show the impacts of different climate losses relative to the no-damage benchmark across economies. Under the average-loss scenario (around 30% agricultural yield loss), low-income economies retain agricultural employment shares that are about 10–15 percentage points higher than in the no-damage path, indicating slower transformation out of agriculture. Middle-income economies are less affected (generally below 5 percentage points), while high-income economies show close-to-zero effects. Under the high-loss scenario (around 70% yield loss), the slowdown becomes larger: low-income economies are about 15–25 percentage points above the no-damage benchmark, middle-income economies around 5 percentage points, and high-income economies remain only weakly affected.

Climate’s impacts on agricultural and aggregate productivity across economies.

Figure 11 extends the evidence presented earlier for low, middle, and high income economies by showing how climate-damage impacts vary across a broader set of countries along the income distribution. The figure confirms the same core pattern: agricultural productivity losses are substantially larger in poorer economies, while richer economies experience smaller losses and offset a larger share through adaptation. Agricultural TFP substantially declines around 10%-15% and 25%-30% for economies at the lowest income levels under 30% and 70% yield loss scenarios respectively. The effects becoming smaller for higher-income economies with the loss of around 5% and 10% under 30% and 70% yield loss scenarios respectively.

While farms in richer economies mitigate a large fraction out to 70%-80% of climate dam-

Figure 11: Impacts of Climate Damages on Agricultural Productivity



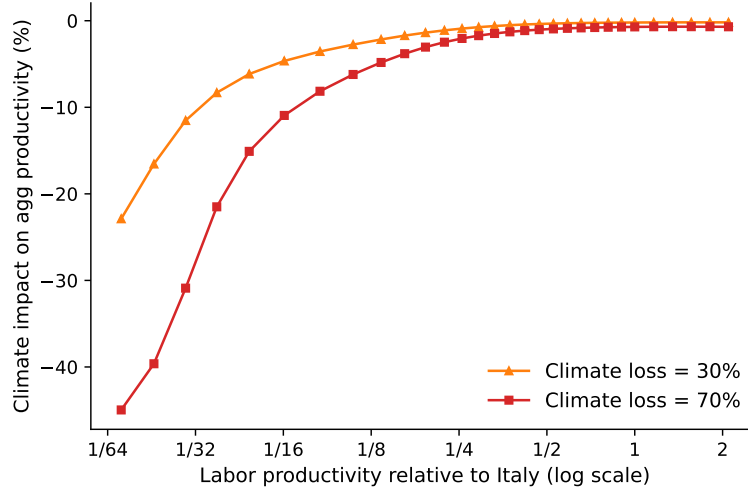
Notes: Agricultural TFP is computed as $Y_a/(N_a^{1-\gamma}L^\gamma)$. %ΔAgricultural TFP is reported as the percentage change in each climate-damage scenario (30% and 70% yield loss) relative to the zero-damage scenario. Average farm-level TFP losses mitigated by adaptation is the average share of climate-induced productivity losses offset by endogenous investment in adaptation technologies across farms.

ages through endogenous adaptation investment, farms in lower-income economies mitigate a limited share, only around 15% of the climate losses. Unequal adaptation capacity is a key mechanism behind the larger climate damages on farm-level and sectoral productivity in low-income economies.

Given the large employment share in agriculture and the larger farm-level productivity losses caused by lower adaptation investment, climate change generates much larger aggregate effects in poorer economies. Figure 12 shows how these damages to agricultural productivity translate into economy-wide labor productivity across economies with different income levels. The aggregate effect is close to zero in rich economies under both climate-damage scenarios, while low-income economies face losses of roughly 10%–20% under the 30% yield-loss scenario and up to about 30%–40% under the 70% yield-loss scenario.

Climate damages and food insecurity We now examine the effect of climate change on food insecurity. We note that in our static framework, food insecurity is a label for the share of population close to subsistence needs (e.g., low levels of agricultural consumption). We pose a simple functional form for the food security threshold to increase with aggregate labor

Figure 12: Impact of Climate Damages on Aggregate Labor Productivity



Notes: The plot reports the percentage change of aggregate labor productivity in each climate-damage scenario (30% and 70% yield loss) relative to the zero-damage scenario.

productivity:

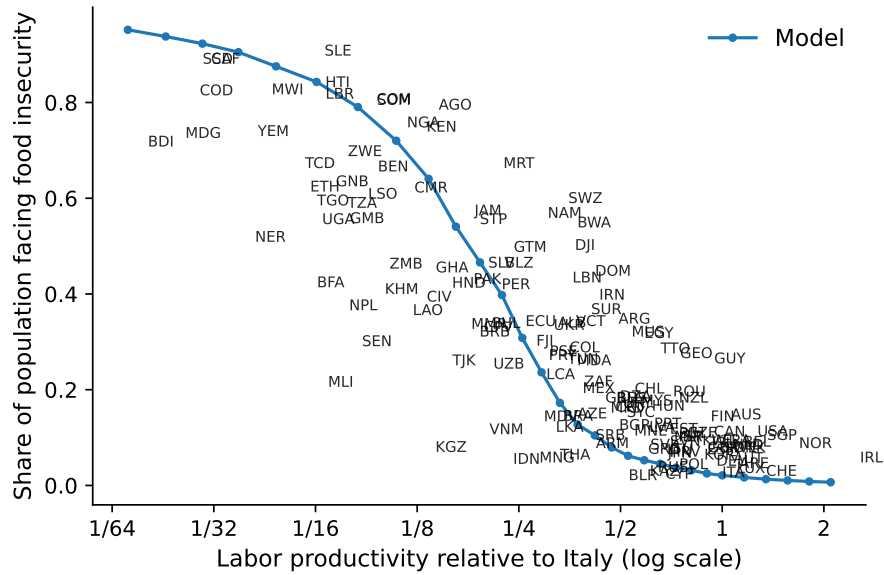
$$\bar{a}(Y) = \bar{a}_0 + \bar{a}_1 \left(\frac{Y}{Y_{BE}} \right).$$

We choose $\bar{a}_0 = 0.05$ and $\bar{a}_1 = 0.05$ to capture the relationship between aggregate labor productivity and food insecurity observed in the cross-country data, see Figure 13. Under this calibration of the food insecurity threshold, the poorest countries in the sample have a food security threshold of approximately 0.051, while the benchmark economy has a threshold of 0.10. This parameterization of food insecurity only matters for deriving distributional implications of climate change and has no real macroeconomic effects.

Table 10 summarizes the results of climate-damage scenarios on food insecurity for both the on-impact and productivity growth cases. On impact, in the medium damage scenario ($D = 0.3$), food insecurity increases by 2.4 p.p. and 6.9 p.p. in low- and middle-income economies, whereas only 0.46 p.p. in the high benchmark economy. The high-damage scenario ($D = 0.70$) amplifies these patterns: food insecurity increases by 4.7 p.p. and 15.4 p.p., in the low and middle income economies, whereas only 1.04 p.p. in the high income benchmark economy.

Regarding the productivity growth scenario discussed earlier, we first report the zero climate

Figure 13: Food Insecurity across Countries, Model vs. Data



Notes: The share of the population experiencing moderate or severe food insecurity against labor productivity relative to Italy. Because the available data are not fully consistent across countries and years, we normalize labor productivity by Italy's labor productivity in the same reported year. Data on aggregate labor productivity are from PWT 11.0 data on food insecurity are from FAOSTAT.

loss baseline, where productivity growth would substantially reduce food insecurity, especially in low and middle income countries. With climate damages, food insecurity rises relative to the no-damage benchmark, again most strongly in poorer economies: the food-insecure share increases by 5.90 and 13.24 percentage points in low-income economies under 30% and 70% damage, versus 1.79 and 3.76 in middle-income economies, and only 0.12 and 0.28 in high-income economies.

Similarly with the earlier results on structural transformation and productivity convergence, progress on food security from productivity growth is substantially undermined by climate damages in less developed economies and Figure 14 reports these results for a broader set of economies along the development spectrum. Panel 14a shows the share of population facing food insecurity across countries under different climate-loss scenarios. In the no-damage scenario, projected productivity growth over 50 years leads to substantial declines in food insecurity, especially in poorer economies. Low-income economies reduce food insecurity from around 80% of the population to about 40%. Middle-income economies decline from roughly 40% to below

Table 10: Climate Change and Food Insecurity

	30% climate damage			70% climate damage		
	Low-	Middle-	High-	Low-	Middle-	High-
(1) On impact of climate damages						
Share of population (change in p.p):						
Food insecurity	2.39	6.91	0.46	4.70	15.35	1.04
Productivity growth scenario to 2050:						
(2) Zero climate loss baseline						
Share of population (change in p.p):						
Food insecurity	-49.6	-40.3	-1.5	-49.6	-40.3	-1.5
(3) Climate damages relative to (2)						
Share of population (change in p.p):						
Food insecurity	5.90	1.79	0.12	13.24	3.76	0.28

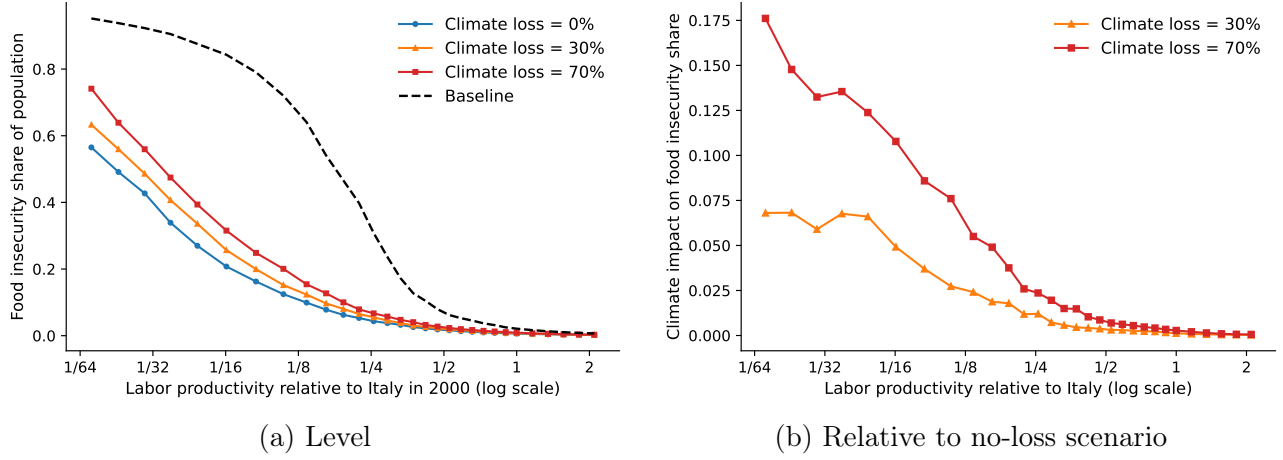
Notes: Low-income economy has $(A, \kappa) = (0.12, 0.18)$; middle-income has $(A, \kappa) = (0.26, 0.33)$; high-income is the benchmark economy with $(A, \kappa) = (1.00, 1.00)$. All outcomes are computed as changes relative to the same economy under no climate damage ($D = 0$). Aggregate labor productivity is measured using the relative price of non-agriculture of the benchmark economy and normalized by the benchmark economy output at $D = 0$. Agricultural TFP is computed as $Y_a/(N_a^{1-\gamma}L^\gamma)$. Average productivity losses mitigated by adaptation is computed as the percentage of climate loss mitigated by endogenous investment in technology on average across farms.

20%. High-income economies start with very low food insecurity shares and exhibit limited additional changes. These patterns indicate that long-run technological progress is a major force improving food security outcomes.

Panel 14b shows the impacts of climate losses relative to the no-damage benchmark. Under the average-loss scenario (around 30% agricultural yield loss), low-income economies have food insecurity rates about 10–15 percentage points higher than in the no-damage path, while middle-income economies are about 3 percentage points higher. Under the high-loss scenario (around 70% yield loss), the gap widens: low-income economies are about 20–25 percentage points above the no-damage benchmark, and middle-income economies are around 5 percentage points above. High-income economies remain only weakly affected. Overall, climate change materially weakens projected improvements in food security, with the largest burden concentrated in poorer countries.

The quantitative results highlight the importance of productivity growth for structural trans-

Figure 14: Projected Food Insecurity across Economies



Notes: Panel (a) plots the agricultural employment share against labor productivity relative to Italy in 2000. Panel (b) plots the differences between agricultural employment share in climate damage scenarios vs. the no damage scenario. The x-axis shows the aggregate labor productivity relative to the benchmark economy in 2000.

formation, land consolidation into larger farms, aggregate productivity convergence, and for mitigating the negative effects of climate change. As discussed earlier, our common productivity growth scenario across economies is conservative relative to the observed disparities in productivity growth rates across countries. Countries with faster productivity growth than our baseline would be able to mitigate a larger proportion of climate damages, whereas countries with lower or no productivity growth would bear the blunt of climate change closer to the on-impact effects of climate damages. These effects, in addition to heterogeneity on the actual impact of climate change across countries, would produce substantial uneven effects of climate change and widening the income disparities across countries.

6 Conclusion

We studied how climate damages differ across countries at different stages of development through differences in farm structure and adaptation. We showed that low-income countries are characterized by smaller farms and higher agricultural employment, facing greater exposure to food insecurity. Using farm-level evidence from Italy, we documented that smaller farms

invest substantially less in adaptation technologies and consequently experience larger climate-related productivity losses.

We then incorporated this evidence into a structural transformation model with heterogeneous farm sizes, climate-induced declines in agricultural productivity, and endogenous adaptation investment. We calibrate the model to Italian farm-level and aggregate data and use it to quantify the macroeconomic implications of climate damages across countries.

Under plausible climate and growth scenarios, limited adaptation investment slows the reallocation of labor out of agriculture in developing countries, delaying structural transformation. This mechanism also slows convergence in aggregate labor productivity and under a less optimistic growth scenario can lead to widening cross-country income gaps.

Interestingly, in the 50-year growth scenario we find that the climate impacts are relatively small in magnitude relative to the impact of compounded productivity. This suggests that the same policies addressing the food problem by enhancing productivity in the agricultural sector, are effective in helping economies deal with the effects of climate change. Similarly, technological advances in mitigation technologies can also be effective. We have shown a wide range of climate damages at all points of the income distribution, whereas our experiments impose the same climate shock in all economies. Assessing heterogeneous climate shocks can be relevant in addressing the implications for the disparity in macroeconomics outcomes across countries. We leave these important areas of inquiry for future research.

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Online Appendix

A Descriptives

Table A.1: Summary Statistics from Italian Farm-Level Data

Variable	Mean	SD	Median	Min	Max	<i>N</i>
Farm size (hectares)	30.20	45.07	14.92	0.10	944.77	85,423
TFP (log)	0.023	0.789	0.027	-1.808	1.926	85,423
$\Delta\log(\text{TFP})$	-0.029	0.641	-0.012	-2.391	2.333	61,007
$\log(\text{Drip} + 1)$	0.303	0.743	0.000	0.000	4.879	85,422
Temperature anomaly ($^{\circ}\text{C}$)	-0.053	0.779	-0.074	-3.159	2.927	61,007
Labor input (hours)	3,563	2,518	2,800	120	70,800	85,398
Agricultural capital (euro)	36,142	67,316	12,720	0	2,201,184	85,423

Notes: The unit of observation is a farm–year. Farm size (winsorized at 0.5 ha) is measured as operated agricultural land in hectares. TFP denotes farm-level total factor productivity in logs, and $\Delta\log(\text{TFP})$ is the annual change in log TFP. $\log(\text{Adapt} + 1)$ measures the intensity of drip (micro-) irrigation use. Temperature anomaly is defined as the deviation of local growing-season temperature from its long-run mean. Labor input is measured in total annual hours worked. Agricultural capital refers to the value of farm capital stocks.

B Robustness of Empirical Findings

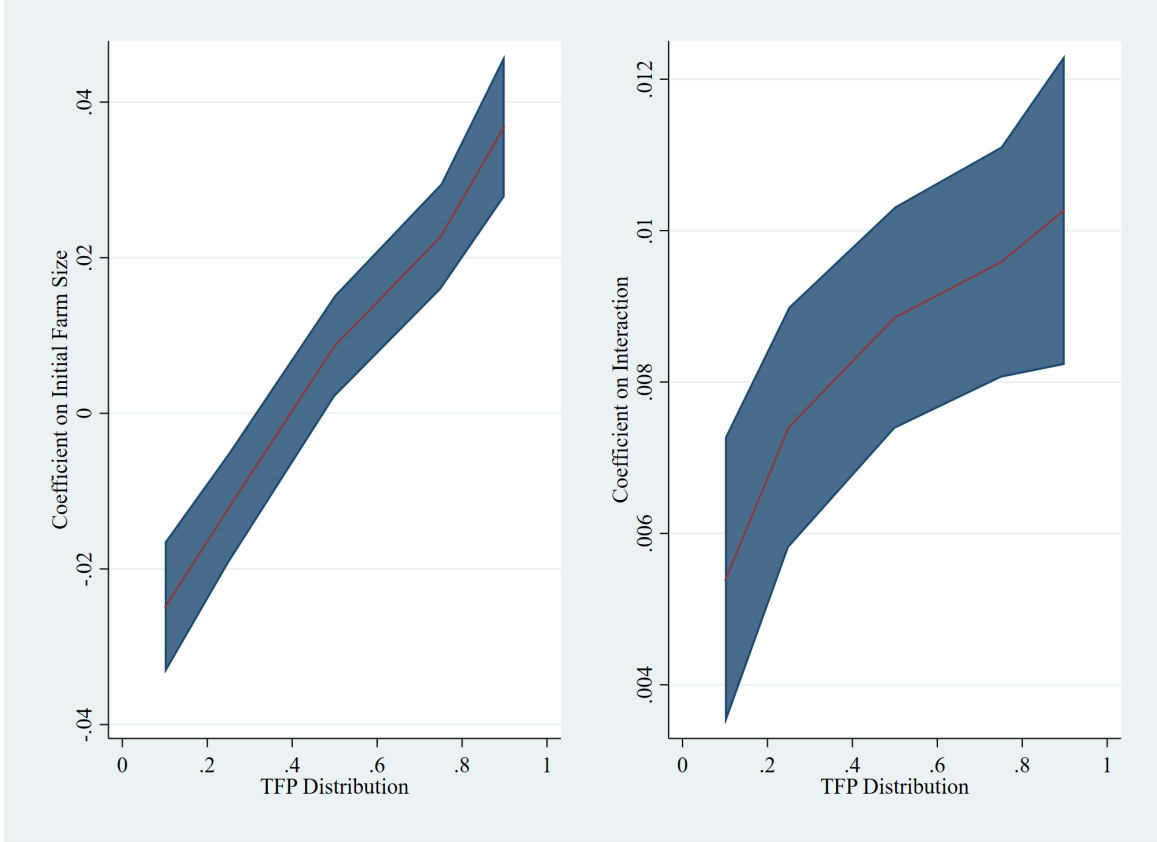


Figure B.1: Heterogeneous effects of farm size and heat exposure across the productivity distribution.

Notes: The figure reports coefficients from quantile regressions, where heat exposure is measured as the number of days with temperatures above 35°C. Quantiles refer to the conditional distribution of farm productivity. The left panel shows that the effect of initial farm size shifts from negative at low productivity levels to positive at higher ones, while the right panel shows that the interaction between size and heat exposure is positive and increasing across quantiles, indicating that larger farms are less affected by heat exposure, especially at higher productivity levels.

Climate Data and Crop-Specific Heat Tolerance To measure farm-level exposure to extreme heat, we follow the logic of Moscona and Sastry and combine high-frequency gridded temperature data with crop-specific temperature thresholds. Daily minimum and maximum temperature are taken from the E-OBS gridded climate dataset for Italy over the period 1995–2024³. Daily minimum and maximum temperature are obtained from the E-OBS gridded climate dataset (version 31.0e) produced by the European Climate Assessment & Dataset project. Specifically, we use the ensemble mean fields of daily minimum temperature (variable `tn`) and daily maximum temperature (variable `tx`) on the 0.1° latitude–longitude grid. The data cover the period 1995–2024 and provide spatially consistent daily temperature observations across Italy. The availability of geographic coordinates for each farm allows us to link these gridded temperature observations directly to the exact latitude and longitude of the farm location. This enables the construction of farm-specific weather exposure measures based on the nearest climate grid cell rather than on aggregated administrative units. Since crop damage from heat is inherently nonlinear and depends on short-lived temperature extremes rather than on annual averages, daily data are essential for our purposes. We focus on the April–October growing season, which corresponds to the period in which the relevant exposure to damaging heat is concentrated. Crop-specific temperature thresholds are obtained from the EcoCrop database made available through FAO/GAEZ.⁴ For each crop, we use the reported upper temperature bound for optimal growth, which we interpret as the maximum temperature that can be sustained without inducing heat stress. These crop-specific thresholds allow the same local weather realization to generate different levels of damaging exposure across crops, depending on their biological tolerance to heat. To link the climate data to farms, we use the geographic coordinates available in the farm-level data and assign each farm to the nearest E-OBS grid cell. We then merge the corresponding annual climate measures to each farm-year observation. This procedure yields a spatially harmonized panel in which each farm is exposed to the weather realization of the closest climate grid point, while differences in crop composition imply different exposure to damaging heat even for farms located in the same area.

Construction of the Heat Exposure Measure Using the daily minimum and maximum temperature series, we construct degree-days above threshold following the approach of Schlenker and Roberts (2009), as implemented in Moscona and Sastry. For each grid cell g , day d , and temperature threshold T , daily temperature is approximated by a sinusoidal curve within the day. Let $T_{min,d,g}$ and $T_{max,d,g}$ denote daily minimum and maximum temperatures, and define the daily mean temperature and amplitude as $T_{avg,d,g} = \frac{T_{min,d,g} + T_{max,d,g}}{2}$, $A_{d,g} = \frac{T_{max,d,g} - T_{min,d,g}}{2}$.

³available at <https://cds.climate.copernicus.eu/datasets/insitu-gridded-observations-europe?tab=download>

⁴available at <https://gaez.fao.org/pages/ecocrop-find-plant>

Daily degree-days above threshold are defined as

$$DD_{d,g}(T) = \begin{cases} 0 & \text{if } T_{max,d,g} \leq T, \\ T_{avg,d,g} - T & \text{if } T_{min,d,g} \geq T, \\ \frac{(T_{avg,d,g} - T)\theta + A_{d,g} \sin(\theta)}{\pi} & \text{otherwise.} \end{cases} \quad (\text{B.1})$$

where $\theta = \cos^{-1} \left(\frac{T - T_{avg,d,g}}{A_{d,g}} \right)$.

This formulation measures not only whether the temperature exceeds the threshold, but also by how much and for what fraction of the day. We repeat this calculation for all integer thresholds between 17°C and 36°C. We then aggregate daily exposure over the growing season (April–October) to obtain annual grid-level degree-days above threshold:

$$DD_{g,t}(T) = \sum_{d \in GS(t)} DD_{d,g}(T),$$

where $GS(t)$ denotes the set of days in the growing season of year t .

To construct crop-specific exposure, each crop k is assigned a maximum temperature threshold T_k^{max} obtained from the EcoCrop database. Crop-specific exposure at the grid-cell level is therefore defined as

$$ExtremeExposure_{g,k,t} = DD_{g,t}(T_k^{max}).$$

Each farm is then assigned the climate realization of the nearest E-OBS grid cell based on geographic coordinates. For a farm i cultivating crop c , crop-specific exposure is given by

$$Exposure_{i,c,t} = ExtremeExposure_{g(i),c,t},$$

where $g(i)$ denotes the grid cell associated with farm i . We follow Moscona and Sastry in constructing crop-specific extreme heat exposure based on degree-days above crop-specific temperature thresholds. Since our unit of observation is the farm rather than the crop at the national level, we aggregate crop-specific exposure using farm-specific initial crop shares instead of national crop area shares.

When farms cultivate multiple crops, farm-level heat exposure is constructed as a weighted average of crop-specific exposure using the farm's initial crop shares. Let s_{ic}^0 denote the share of cultivated surface allocated to crop c in the first year the farm appears in the panel. Farm-

level heat exposure is then defined as

$$HeatExposure_{it} = \sum_c s_{ic}^0 \cdot Exposure_{i,c,t}.$$

Using baseline crop shares ensures that variation in the exposure measure reflects exogenous changes in weather conditions rather than endogenous changes in crop choice over time.

Table B.2: Extreme Heat Exposure, Farm Size, and Farm TFP

	Dependent variable: $\log(TFP_{it})$	
	(1)	(2)
$\log(FarmSize_{it})$	0.267*** (0.012)	
$HeatExposure_{it}$	-0.011* (0.006)	-0.016*** (0.004)
$\log(FarmSize_{it}) \times HeatExposure_{it}$	0.004* (0.002)	
$\log(FarmSize_{i_0})$		0.188*** (0.005)
$\log(FarmSize_{i_0}) \times HeatExposure_{it}$		0.008*** (0.001)
Constant	-0.756*** (0.033)	-0.555*** (0.015)
Observations	64,063	69,404
Farm FE	✓	No
Year $\times$ province FE	✓	✓
Year $\times$ farm type FE	✓	✓

Notes: The unit of analysis is a farm-year. The dependent variable is farm-level total factor productivity, $\log(TFP_{it})$. Heat exposure is measured using the Moscona–Sastry extreme heat index. Column (1) measures farm size as the utilized agricultural area, while column (2) uses intital farm size. For Column (2) results holds even if we control for Farm FE, excluding $FarmSize_{i_0}$ for collinearity. All variable are in log. Farm type refers to the farm’s main production specialization (e.g., cereals, horticulture, permanent crops). Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Heat Exposure, Farm Size, and Adoption of Drip Irrigation (Robustness)

<i>HeatExposure measure:</i>	Dependent variable: $\log(\text{Drip}_{it} + 1)$				
	(1) #Days > 35°C	(2) #Days 30–35°C	(3) #Days > 35°C	(4) #Days 30–35°C	(5) ΔTemp
$\log(\text{FarmSize}_{i0})$	0.075*** (0.003)	0.056*** (0.004)			
HeatExposure_{it}	−0.009*** (0.001)	−0.002*** (0.000)	−0.030*** (0.001)	−0.005*** (0.000)	−0.036*** (0.010)
$\log(\text{FarmSize}_{i0}) \times \text{HeatExposure}_{it}$	0.003*** (0.000)	0.001*** (0.000)	0.010*** (0.000)	0.002*** (0.000)	0.002 (0.003)
Constant	0.105*** (0.007)	0.130*** (0.011)	0.303*** (0.003)	0.276*** (0.005)	0.298*** (0.003)
Year $\times$ farm type FE	✓	✓	✓	✓	✓
Year $\times$ altitude FE	✓	✓	✓	✓	✓
Observations	98,175	98,175	98,175	98,175	69,769
Adj. R^2	0.132	0.132	0.124	0.130	0.120

Notes: The unit of analysis is a farm–year. The dependent variable is the log of drip irrigation adoption, $\log(\text{Drip}_{it} + 1)$. Farm size is measured as initial farm size, $\log(\text{FarmSize}_{i0})$. Heat exposure is alternatively measured as the number of days with temperatures above 35°C, the number of days with temperatures between 30°C and 35°C, and the interannual change in temperature (ΔT). All specifications include year-by-farm type and year-by-altitude fixed effects. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Heat Exposure, Farm Size, and Adaptation (PPML)

	Dependent variable: $\log(\text{Drip} + 1)_{it}$		
	(1)	(2)	(3)
<i>HeatExposure measure:</i>	#Days > 35°C	#Days 30–35°C	ΔTemp
$\log(\text{FarmSize}_{i0})$	0.675*** (0.015)	0.603*** (0.024)	0.686*** (0.016)
HeatExposure_{it}	−0.052*** (0.008)	−0.007*** (0.001)	−0.159*** (0.047)
$\log(\text{FarmSize}_{i0}) \times \text{HeatExposure}_{it}$	0.013*** (0.003)	0.003*** (0.001)	0.016 (0.019)
Constant	−1.029*** (0.041)	−0.943*** (0.060)	−1.128*** (0.041)
Year $\times$ farm type FE	✓	✓	✓
Year $\times$ altitude FE	✓	✓	✓
Observations	98,148	98,148	69,733

Notes: The unit of analysis is a farm–year. The dependent variable is the level of adaptation, Adapt_{it} . Farm size is measured as initial farm size, $\log(\text{FarmSize}_{i0})$. Heat exposure is alternatively measured as the number of days with temperatures above 35°C, the number of days with temperatures between 30°C and 35°C, and the interannual change in temperature (ΔT). All specifications are estimated using a Poisson pseudo-maximum likelihood estimator and include year-by-farm type and year-by-altitude fixed effects. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Heat Exposure, Initial Productivity, and Adoption of Drip Irrigation (Robustness)

<i>HeatExposure measure:</i>	Dependent variable: $\log(\text{Drip}_{it} + 1)$		
	(1) #Days > 35°C	(2) #Days 30–35°C	(3) ΔTemp
$\log(\text{TFP}_{i0})$	0.064*** (0.003)	0.020*** (0.005)	0.073*** (0.003)
HeatExposure_{it}	−0.009*** (0.002)	−0.003*** (0.000)	−0.018* (0.011)
$\log(\text{TFP}_{i0}) \times \text{HeatExposure}_{it}$	0.003*** (0.001)	0.002*** (0.000)	−0.005 (0.004)
Constant	0.151*** (0.008)	0.227*** (0.013)	0.126*** (0.008)
Year $\times$ farm type FE	✓	✓	✓
Year $\times$ altitude FE	✓	✓	✓
Observations	98,057	98,057	69,682
Adj. R^2	0.126	0.128	0.127

Notes: The unit of analysis is a farm–year. The dependent variable is the log of drip irrigation adoption, $\log(\text{Drip}_{it} + 1)$. Initial productivity is measured as $\log(\text{TFP}_{i0})$. Heat exposure is alternatively measured as the number of days with temperatures above 35°C, the number of days with temperatures between 30°C and 35°C, and the interannual change in temperature (ΔT). All specifications include year-by-farm type and year-by-altitude fixed effects. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: First-stage regressions: adaptation and temperature interaction

	(1) IV at $t - 1$	(2) IV at t
<i>Panel A: Dependent variable = $\log(\text{Adaptation})$</i>		
IV(Adaptation)	0.283*** (0.054)	0.291*** (0.052)
IV(Adaptation) $\times$ HeatExposure	0.015 (0.030)	0.002 (0.031)
HeatExposure	-0.225 (0.272)	-0.114 (0.275)
First-stage F (excluded instruments)	17.9	25.6
R^2	0.25	0.27
Observations	3,079	3,270
Year, sector, altitude FE	✓	✓
<i>Panel B: Dependent variable = $\text{HeatExposure} \times \log(\text{Adaptation})$</i>		
IV(Adaptation)	0.026 (0.018)	-0.001 (0.030)
IV(Adaptation) $\times$ HeatExposure	0.286*** (0.069)	0.281*** (0.056)
HeatExposure	-1.158** (0.483)	-1.062*** (0.369)
First-stage F (excluded instruments)	9.6	21.4
R^2	0.44	0.46
Observations	3,079	3,270
Year, sector, altitude FE	✓	✓

Notes: The table reports first-stage regressions corresponding to the IV (2SLS) specifications in Table 4. In Panel A, the dependent variable is $\log(\text{Adaptation}_{it})$; in Panel B, the dependent variable is $\text{HeatExposure}_{it} \times \log(\text{Adaptation}_{it})$. The excluded instruments are the log of EU environmental funds received by the farm (“IV(Adaptation)”) and its interaction with the HeatExposure $\text{HeatExposure}_{it} \times \text{IV(Adaptation)}_{it}$. Column (1) uses instruments measured at $t - 1$; column (2) uses instruments measured at t . All regressions include year, sector, and altitude fixed effects. Standard errors are clustered at the province level. Reported first-stage F -statistics are for the joint significance of the excluded instruments.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests).

C Climate Adaptation Technology $g(D, x)$

We consider several alternative parametric specifications for the damage–adaptation function $g(D, x)$.

(i) Exponential damage with full mitigation. We first consider an exponential form in which adaptation can, in principle, fully offset climate damage. Let $D \in [0, 1)$ denote the productivity loss in the absence of adaptation, so that $g(D, 0) = 1 - D$. We set

$$g(D, x) = 1 - De^{-\eta x}, \quad \eta > 0. \quad (\text{C.2})$$

This specification satisfies

$$g(D, 0) = 1 - D, \quad g(0, x) = 1 \quad \forall x, \quad \lim_{x \rightarrow \infty} g(D, x) = 1,$$

so that a farm with $x = 0$ bears the full damage D , while arbitrarily large adaptation ($x \rightarrow \infty$) restores productivity to its no-damage level. Moreover,

$$g_x(D, x) = D\eta e^{-\eta x} > 0, \quad g_{xx}(D, x) = -D\eta^2 e^{-\eta x} < 0,$$

so adaptation exhibits diminishing returns.

Under the linear profit specification $\pi(sz) = \Omega sz$ derived above and linear cost $c(x) = x$, the first-order condition (??) becomes

$$\Omega s_{ai} D_i \eta e^{-\eta x_i} = 1,$$

which yields the interior optimal adaptation level

$$x(s_{ai}, D_i) = \frac{1}{\eta} \log(\Omega s_{ai} D_i \eta), \quad (\text{C.3})$$

whenever $\Omega s_{ai} D_i \eta > 1$, and $x(s_{ai}, D_i) = 0$ otherwise. This implies that larger and more climate-exposed farms invest more in adaptation.

A convenient feature of (C.2) is that it delivers a simple log-linear representation of $\log g(D, x)$ around the data, which maps directly into reduced-form regressions of log TFP on temperature, adaptation, and their interaction. A limitation is that this specification allows full mitigation: for any given D , sufficiently large x restores $g(D, x)$ arbitrarily close to 1.

(ii) Exponential damage with partial mitigation. To allow for residual climate damages even under very high adaptation, we introduce a parameter $\underline{\phi} \in (0, 1)$ capturing the minimal damage share that cannot be mitigated. We set

$$g(D, x) = 1 - \left[\underline{\phi} + (1 - \underline{\phi})e^{-\eta x} \right] D, \quad 0 < \underline{\phi} < 1, \eta > 0. \quad (\text{C.4})$$

This form satisfies

$$g(D, 0) = 1 - D, \quad g(0, x) = 1 \quad \forall x, \quad \lim_{x \rightarrow \infty} g(D, x) = 1 - \underline{\phi} D,$$

so that only a fraction $1 - \underline{\phi}$ of the damage D can be eliminated, and a residual share $\underline{\phi} D$ remains even as $x \rightarrow \infty$. Adaptation remains increasing and concave:

$$g_x(D, x) = (1 - \underline{\phi}) D \eta e^{-\eta x} > 0, \quad g_{xx}(D, x) = -(1 - \underline{\phi}) D \eta^2 e^{-\eta x} < 0.$$

The parameter $\underline{\phi}$ has a transparent interpretation,

$$\underline{\phi} = \frac{\text{residual damage under arbitrarily high adaptation}}{\text{damage with no adaptation}},$$

and we therefore treat $\underline{\phi}$ as an externally calibrated parameter, using quantitative estimates of the maximal fraction of climate damages that can be avoided through adaptation in the agricultural sector. Given $\underline{\phi}$, the remaining parameters (δ, η) can be estimated by matching the model-implied response of log TFP to temperature, adaptation, and their interaction to the reduced-form coefficients.

(iii) Hyperbolic damage with partial mitigation. An alternative specification replaces the exponential attenuation with a rational function, which decays more slowly in x :

$$g(D, x) = 1 - D \left[\underline{\phi} + (1 - \underline{\phi}) \frac{1}{1 + \eta x} \right], \quad 0 < \underline{\phi} \leq 1, \eta > 0. \quad (\text{C.5})$$

Again,

$$g(D, 0) = 1 - D, \quad g(0, x) = 1 \quad \forall x, \quad \lim_{x \rightarrow \infty} g(D, x) = 1 - \underline{\phi} D,$$

so that only a fraction $1 - \underline{\phi}$ of damage can be mitigated. The marginal effect of adaptation is

$$g_x(D, x) = D(1 - \underline{\phi}) \frac{\eta}{(1 + \eta x)^2} > 0,$$

with $g_{xx}(D, x) < 0$, implying diminishing returns to adaptation.

Relative to the exponential case, the hyperbolic form implies that mitigation effects taper off more gradually for large x , which can be desirable in counterfactuals that consider large changes in adaptation. Moreover, expanding $\log g(D, x)$ around the sample mean of (D, x) yields a log-linear approximation in temperature, $\log x$, and their interaction, closely aligned with the empirical specification used in our regressions. As in (C.4), the parameter $\underline{\phi}$ can be calibrated from external evidence on residual damages, while η is disciplined by the estimated elasticity of $\log$ TFP with respect to adaptation and its interaction with temperature.

(iv) Regression-consistent wedge. To match the reduced-form specification

$$\log \text{TFP}_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 \log x_{it} + \beta_3 (T_{it} \log x_{it}) + \varepsilon_{it},$$

we assume that the climate–adaptation multiplier takes the form

$$z_i = g(T_i, x_i) = \exp(-D(T_i)) x_i^{\psi + \eta D(T_i)},$$

so that

$$\log z_i = -D(T_i) + D(T_i) \eta \log x_i + \psi \log x_i.$$

With the linear damage index $D(T) = \delta T$, this implies

$$\log \text{TFP}_{it} = \alpha_i - \delta T_{it} + \delta \eta T_{it} \log x_{it} + \psi \log x_{it},$$

and therefore

$$\beta_1 = -\delta, \quad \beta_2 = \psi, \quad \beta_3 = \delta \eta.$$

The specification has several advantages and disadvantages.

Pros.

- **Direct link to the reduced form.** With a linear damage index $D(T) = \delta T$, the model reproduces exactly the empirical regression

$$\log \text{TFP}_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 \log x_{it} + \beta_3 (T_{it} \log x_{it}) + \varepsilon_{it},$$

with a one-to-one mapping

$$\beta_1 = -\delta, \quad \beta_2 = \psi, \quad \beta_3 = \delta \eta.$$

Thus the estimated coefficients $(\beta_1, \beta_2, \beta_3)$ can be interpreted directly as structural parameters (δ, η, ψ) .

- **Transparent interpretation.** The term $-D(T)$ captures the pure effect of temperature on productivity, $D(T) \eta \log x$ captures the fact that adaptation is more valuable in hotter conditions, and $\psi \log x$ allows for a (possibly small) direct productivity effect of adaptation even in the absence of climate damage.
- **Tractability and closed-form decisions.** Under the linear profit specification $\pi(sz) = \Omega sz$ and linear cost $c(x) = x$, the first-order condition for adaptation,

$$\frac{\partial}{\partial x} [\Omega s g(T, x)] = 1,$$

becomes

$$\Omega s \exp(-D(T)) x^{\psi + \eta D(T) - 1} (\psi + \eta D(T)) = 1,$$

which yields a closed-form expression for $x(s, T)$ whenever $\psi + \eta D(T) \neq 1$. This facilitates comparative statics and quantitative counterfactuals.

- **Monotonicity in adaptation.** For $D(T) \geq 0$ and $\psi + \eta D(T) > 0$, we have

$$\frac{\partial \log z}{\partial \log x} = \psi + \eta D(T) > 0,$$

so that an increase in adaptation x always raises climate-adjusted productivity.

Cons.

- **No built-in partial mitigation.** For fixed $T > 0$ and $\psi + \eta D(T) > 0$, we have $z(T, x) \rightarrow \infty$ as $x \rightarrow \infty$. Hence adaptation can more than fully offset climate damage and raise TFP arbitrarily above the no-damage benchmark. This may be at odds with the idea that even very large adaptation efforts cannot completely undo climate change, or that there is an upper bound on feasible productivity.
- **Marginal effect of temperature can change sign at high adaptation.** The marginal effect of temperature on log productivity is

$$\frac{\partial \log z}{\partial T} = -D'(T) + D'(T) \eta \log x = D'(T) (\eta \log x - 1).$$

For moderate x (so that $\eta \log x < 1$) this is negative, as desired. However, for sufficiently large x the model implies $\partial \log z / \partial T > 0$, i.e. additional warming becomes beneficial once adaptation is very high. Empirically, the parameter estimates may ensure that this region is far outside the observed support of x , but the possibility is present in the functional form.

- **Adaptation at zero damage if $\psi > 0$.** When $D(T) = 0$, we obtain $z(0, x) = x^\psi$. If $\psi > 0$, adaptation has a strictly positive effect on productivity even in the absence of climate damage, and with linear costs the optimal choice $x(0)$ is strictly positive. This violates the normative condition that farms would not invest in climate adaptation when there is no climate risk. One can enforce $x(0) = 0$ by imposing $\psi = 0$ in the structural model and treating a small estimated β_2 as capturing other, unmodeled channels.
- **Unbounded gains in extreme counterfactuals.** Because $z(T, x)$ grows without bound in x for any fixed $T > 0$, aggressive adaptation policies in counterfactual simulations (very large x) can generate unrealistically large productivity gains. If the analysis focuses on moderate changes around the observed range of (T, x) , this may be of limited concern, but for large departures from the data a bounded specification (such as the hyperbolic or exponential partial-mitigation forms discussed above) may be more appropriate.