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Growth with Mismatch – Theory and Evidence from TFP Estimates

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Abstract

To date, goods market inefficiency in terms of mismatch has not played a role in economic growth analyses. The idea of ongoing market mismatch has so far gained little attention, even in the discussion of sluggish growth in recent decades. In this paper we thus suggest a stylized endogenous growth model that includes aggregate goods market mismatch. Mismatch and efficiency losses are the result of the stochastic interaction between supply and demand side elements. As a result, growth is not purely supply side driven: the demand side also matters. Thus, this approach can bridge the gap between endogenous growth modeling and Keynesian demand side approaches. Further, based on this growth model with mismatch we suggest that aggregate market mismatch can be identified in TFP estimations. Departing from a standard TFP estimation containing major key drivers, the match efficiency rate – an output gap-based indicator – is introduced to indicate mismatch. With an instrumental variable panel regression and using a yearly panel data set for 19 developed countries between 1985 and 2019 and 1996 and 2019, respectively, we indeed identify a significant effect of market mismatch on TFP and, therefore, the growth path.

Key words: TFP, growth models, market mismatch, output gap, instrumental variables **JEL classification numbers:** C33; C36; O40; O47

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1 Introduction

The demand side has no role to play in today's mainstream growth theory. Technical innovations, or factors that can be accumulated, determine potential production, and customers fully absorb whatever is potentially available in the economy. Where there is automatically sufficient demand, savings are fully channeled into investments, and investments are made in those factors that generate the capacity for more production and growth.

This story holds in the neoclassical Solow-Swan type of growth as well as in endogenous growth theory, which is relevant for this paper. Endogenous growth theory started with the models proposed by Romer (1986, 1987, 1990) and Lucas (1988), and has since become the dominant approach to growth. The most prominent attribute of endogenous growth theory is the ability to generate a sustainable and constant growth rate via various mechanisms (often scale economies) and to select this sustainable growth rate as the optimal intertemporal choice. As Aghion et al. (1998), Jones (1999), Aghion and Durlauf (2005), and Aghion and Howitt (2008) provide excellent reviews and descriptions of these mechanisms, there is no need to repeat their comprehensive, detailed discussions here.

But how can growth economists be so sure that only the supply side determines growth? Why is it so difficult to consider that another mechanism may allow the demand side to play a role? There is indeed a strand of literature in the Keynesian tradition that focuses on the demand side. It began with the pioneering work of Harrod (1939) and Domar (1946) and continues up to the more recent work of, for example, Dutt (2006) and Palley (1996, 1997, 2014). In these models growth is demand-driven. Moreover, in the recent debate on the Great Recession and Secular Stagnation, some arguments go beyond discussing the supply side. Summers (2014), for instance, raises concerns about a systematic savings-investment mismatch that may be one of the causes of Secular Stagnation. Gordon (2012, 2015) emphasizes that increasing inequality may also relate to effects on the demand side.

In our approach, that is of growth with mismatch, we combine elements from the two strands of thinking, i.e., the neoclassical and Keynesian traditions. We combine the supply side processes, taken from a stylized model of endogenous growth, with an independent Keynesian demand side, making the demand side equally as important. While standard growth theory assumes that allocation is perfect in the long-term

growth process, such that all resources contribute to aggregate output, we focus on continuous allocative imperfections in the long-term as well. That said, we want to modify the growth mechanism itself and turn to a growth process in which the demand side has a key role to play in the long-term steady-state process.

To the best of our knowledge, there is no macroeconomic theoretical modeling that includes goods market imperfections in aggregate growth models. While Jones (2021) recently argued in favor of misallocation at the firm level that ultimately affects aggregate TFP and growth,¹ we argue for a broader and continuing matching problem that includes firms' and consumers' information and search activities. In a growing economy, new goods are continuously introduced to markets, while other goods simultaneously disappear. Thus, ongoing search and information activities are necessary in these continuously changing markets. Both firms and customers have to put a bit of effort into the matching process. Firms have to make search efforts to find customers, and customers have to acquire information to find the appropriate goods. To focus on this idea, we add an aggregate goods market matching mechanism to the simple endogenous growth mechanics of Jones (2021). Potential mismatch can be eliminated through appropriate resource allocation. However, where resources are allocated to the matching procedure, effective production is less than potential production. The more resources are needed to eliminate the mismatch, the larger the gap between effective and potential output. Thus, in this model, allocative imperfection is due to mismatch and the matching process. Further, as the matching mechanism is determined by both aggregate supply and demand, the demand side plays a major role for the equilibrium growth path below potential output.

Within this matching mechanism, interdependencies between demand and supply matter for matching efficiency, and thus for allocation in the long-term economic growth process. Modeling growth with mismatch allows us to combine purely supply side-driven standard growth modeling with demand side elements, and thus we suggest a kind of hybrid model that incorporates endogenous growth modeling and Keynesian views on the role of the demand side.

The essence of our paper is threefold: (1) We suggest a very simple model of

¹Based on his growth model, he discusses the idea that misallocation has been responsible for a significant part of TFP growth in the US since the 1950s. Following Hsieh et al. (2019), but in contrast to Bils et al. (2020), Jones (2021) argues in favor of decreasing misallocation in the US. Based on a yearly growth rate of 2% in the US since the 1950s, TFP accounts for 1.3 percentage points, of which 0.3 percentage points reflect misallocation.

endogenous growth based on the stylized model provided by Jones (2021). (2) We include a stochastic mismatch that relates to the demand side as a potentially constraining element even in the steady state of the otherwise standard endogenous growth mechanics. Potential growth is driven by the supply side, but mismatch in final goods markets and a matching mechanism lead to interaction between the demand and the supply side, such that growth can be demand-restricted. (3) According to our theory, mismatch and imperfect allocation reduce total factor productivity (TFP). Consistent with empirical growth analysis, we turn to TFP growth and empirically test our model². We use a sample of 15 advanced economies in the period up to 2019 and incorporate the match efficiency rate, that is the ratio of current effective to potential output, into instrumental variable panel regressions. This match efficiency rate – an output gap-based indicator – measures how imperfect the allocation is in the current equilibrium. Other potential control variables are introduced based on Kim and Loayza (2019) reviewing TFP-affecting factors. As proposed by our theoretical model, TFP can be significantly explained by the proposed indicator and thus market mismatch. Therefore, we also find empirical evidence that match efficiency, and thus the demand side, is an important ingredient of TFP and economic growth.

The remainder of this paper is structured as follows: Section 2 shows our growth with mismatch model and derives the match efficiency rate that is a proxy for the effects of the matching process. Section 3 provides the empirical analysis that stresses the results of the theoretical model presented here. An overview and an explanation of the selected variables are provided. Section 4 summarizes and concludes.

²Identifying the impact of misallocation on TFP has to some extent already been empirically examined. However, the role of the business cycle and aggregate demand is neglected. Restuccia and Rogerson (2013) identify two approaches that empirically address misallocation and TFP: a direct and an indirect one. While the direct approach explicitly picks out factors that could be important sources of misallocation, the indirect approach tries to gather "the net effect of the entire bundle of underlying factors on misallocation" (ibid.: 4). The literature that adopts the direct approach reflects the misallocation of labor due to firing taxes (Hopenhayn and Rogerson 1993), employment policies (Lagos 2006), firm size policy (Guner et al. 2008), trade barriers (Alcalá and Ciccone 2004, Epifani and Gancia 2011, Lileeva and Treffer 2010), and credit market imperfections (Banerjee and Duflo 2005). The indirect approach centers around Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), where differences in marginal revenue products across countries result in TFP differences.

2 A Model of Growth with Goods Market Mismatch

While TFP is a central element in economic growth, market efficiency as a driver or reducer of TFP has so far been largely disregarded in growth theory. This section outlines a model of growth in which market inefficiencies are explicitly included. That said, instead of arguing only in favor of the afore-mentioned misallocation, we argue that market matching and allocative efficiency require search activities on both the supply and the demand side. An efficient match does not come for free; instead, it is the result of active resource use. With this notion, we are in line with the strand of literature that follows the indirect approach. If an economy needs strong search activities for an efficient matching process, growth is affected via TFP performance. Thus, in Section 3 we provide empirical evidence for the hypothesis that misallocation and market inefficiency play a role for TFP.

2.1 Production and Supply

As we want to introduce matching activities as a major idea in the simplest way possible, we are fortunate that Jones (2021) already cleared the way in sketching out the core of semi-endogenous and, as a special case, endogenous growth mechanics. We briefly review this model in Appendix A. Here, we modify some of his assumptions to develop a simple, stylized model of growth with mismatch. As a first step we import equation (A1) in Appendix A from the Jones (2021) model. According to this very simple linear one-factor production function, a representative firm produces output³

$$Y(t) = N(t) L_Y(t) \tag{1}$$

with labor in production $L_Y(t)$ and technology indicated by $N(t)$. However, (1) differs slightly from (A1) in the Jones model. In the Jones model's production function the variable $A(t)$ is a general, unspecified technology index. We want to use a more specific interpretation of existing technologies that is closer to Romer (1986, 1987). In our model, $N(t)$ is the number of technology representing goods that have been successfully introduced into the economy. An increase in $N(t)$ implies that

³Note that we already set $\sigma = 1$, as we want to model an even simpler endogenous growth process.

larger aggregate output can be produced with the same aggregate labor input and, hence, indicates technical progress and productivity growth (see section 2.4). Thus, $N(t)$ still indicates technology even if the interpretation is more specific.

2.2 Income and Demand

Income and Labor Rewards As in Jones (2021), the economy has a given amount of homogeneous labor $L = 1$. We assume that a representative household has three occupations that are described by the labor share in production l_Y , the labor share in firms' sales and matching activities l_ϕ , and a given⁴ labor share in research and development (R&D) activities \bar{l}_R

$$1 = l_Y + l_\phi + \bar{l}_R. \quad (2)$$

As only labor in production generates real output and labor is the only input factor and homogeneous, all real output is rewarded as labor income for the representative household. Thus, the household's wage rate is $w(t) = \frac{Y(t)}{L}$ and total (labor) income is

$$w(t) L = Y(t) = N(t) l_Y(t) L.$$

Consumers As the government collects taxes at rate τ , households spend the given ratio c of their disposable income on consumption. However, when searching for consumption goods they need information about these goods and also spend the endogenous income share θ on the respective information goods. Total consumption-related expenditure is, hence, denoted by C and adds up to

$$C(t) = (c + \theta) (1 - \tau) Y(t). \quad (3)$$

Investment Private investment expenditures I are incurred when preparing the market entry of new products. While \dot{A} denotes the number of new business ideas, each attempted market entry of a new product requires an investment expenditure v . Thus, attempting to launch $\dot{A}(t)$ new product ideas on the market generates total

⁴Again, see the Jones model in the Appendix A, with \bar{l}_R as the share of labor in R&D, $L_R = \bar{l}_R L$.

investments⁵ as

$$I(t) = v\dot{A}(t). \quad (4)$$

Government Expenditure In this economy, the government exogenously determines its expenditure G . Since the government's budget deficit is defined as zero, expenditure directly determines tax policy. A change in government expenditure directly implies a change in tax rate τ . Thus, for a balanced budget we obtain

$$\tau Y(t) = G(t). \quad (5)$$

If we divide (5) by $Y(t)$, we see that the government's exogenous rate of expenditure $g = G/Y$ determines the tax rate τ that is required for a balanced budget

$$\tau = g. \quad (6)$$

Keynesian Income-Expenditure Equilibrium In an economy with a balanced government budget and a random demand shock $\varepsilon(t)$, we obtain a standard Keynesian multiplier for the income-expenditure equilibrium

$$Y^D(t) = \frac{v\dot{A}(t) + \varepsilon(t)}{(1-c-\theta)(1-g)}, \quad \text{with } E[\varepsilon] = 0. \quad (7)$$

However, for a macroeconomic equilibrium we need to look at the demand and the supply side. If $\lambda(t)$ is the *excess demand ratio*

$$\lambda(t) = \frac{Y^D(t)}{Y(t)}, \quad (8)$$

in *aggregate market equilibrium* the expected value of $\lambda(t)$ turns to 1,

$$E[\lambda(t)] = \frac{E[Y^D(t)]}{Y(t)} = 1. \quad (9)$$

⁵In this simple modeling, we refer to firms' expenditure for market entry as investments even if there is no accumulated capital.

2.3 Mismatch

Firms' Perception of Mismatch A firm i produces output Y_i and may observe that only fraction ϕ_i can be immediately sold on the market. That is, only $\phi_i Y_i$ of the output instantly finds a customer. In a world of imperfect information, firms perceive this lack of sales as a mismatch in their market, such that the firms' mismatch ratio δ_i determines the effective sales ratio

$$\phi_i(t) = 1 - \delta_i(t). \quad (10)$$

That is, at the current level of search and information acquisition, δ_i is the ratio of goods that are produced but have yet to find a customer.

Firms' Counter-measures As we assume that the mismatch ratio is a stochastic variable, the sales ratio is also a random variable. However, firms also know that the problem of not selling their goods is due to a mismatch in their market; this mismatch can, however, be improved by means of individual match-improving measures m_i , which each firm can introduce⁶. Firms collect information, adjust their products to customers' tastes, inform customers about their products, or search for new customers, etc. Entire sales departments are deployed (l_{ϕ_i}) to improve the match between the firm's produced goods and customer demand. If $\delta'_i(t)$ is the firm's given stochastic mismatch ratio and $m_i(l_{\phi_i})$ is the match-improving counter-measure that is determined by labor in sales and matching activities l_{ϕ_i} , then the firm's mismatch ratio is

$$\delta_i(t) = \delta'_i(t) - m_i(l_{\phi_i}). \quad (11)$$

Further, when a firm has produced more than it can currently sell (for $\phi_i < 1$), we assume that the marginal expected revenue with respect to labor is larger for sales activities than for production. That is, condition⁷

$$\eta_{E[\phi_i], l_{\phi_i}} > \eta_{Y_i, l_{Y_i}} \frac{l_{\phi_i}}{l_{Y_i}} \quad (12)$$

⁶Note that in standard modelling, prices do the complete adjustment toward equilibrium. While we do not deny that prices and price adjustments are important mechanisms, we suggest that there is more to this. From labor market matching theory, we learn that mismatch and imperfect information can play a role. That is what we suggest is the case for goods markets as well, and is why we focus on this other mechanism.

⁷For a detailed explanation, see the Appendix B.

must hold. In other words, each firm always reallocates labor from production to sales up to the point at which all produced goods can be sold and the effective sales ratio turns into

$$E[\phi_i(t)] = 1. \quad (13)$$

Idiosyncratic and Aggregate Roots of the Mismatch Now we need to move from the purely individual perspective (11) to the full description of the mismatch. We argue that the mismatch is determined by two elements: (i) an idiosyncratic component for each individual firm providing its goods and (ii) an aggregate market component.

(i) First, sales problems are due to firm i -specific or idiosyncratic obstacles in the respective firm's market. We assume an idiosyncratic information problem that is denoted by the random variable ε_{Fi} , with $1 > E[\varepsilon_{Fi}] > 0$.

(ii) The second (aggregate) component is a potential stochastic *shortage of aggregate demand* $\Delta^D(t)$. From an individual firm's perspective, a shortage in aggregate demand makes it more difficult to find customers.⁸ Thus, the shortage in aggregate demand indicates tightness in the aggregate market, which also affects the individual market mismatch. So we define the *aggregate demand gap* as

$$\Delta^D(t) = \frac{Y(t) - Y^D(t)}{Y(t)} = 1 - \lambda(t). \quad (14)$$

Therefore, the mismatch that is perceived by each firm i is a combination of the idiosyncratic driver and the aggregate market driver and can be described as

$$\delta'_i(t) = \Delta^D(t) \varepsilon_{Fi}. \quad (15)$$

Next, we have to aggregate to link up these individual conditions and activities with total market conditions to determine the overall expected market mismatch a firm experiences. If we now assume that ε_{Fi} are i.i.d. for $i \in \mathcal{I}$, we can aggregate ($\varepsilon_{Fi} = \varepsilon_F$,) to obtain the *expected mismatch* for a now representative firm and its market

$$E[\delta'(t)] = (1 - E[\lambda]) E[\varepsilon_F] - cov(\lambda, \varepsilon_F), \quad \text{with } cov(\lambda, \varepsilon_F) < 0. \quad (16)$$

⁸This assumption adopts ideas from labor market matching theory, which frequently suggests that larger market demand eases a match.

We assume that $cov(\lambda, \varepsilon_F)$ is negative because a random increase in aggregate demand ε trickles down to each firm's market demand, reduces the tightness in each firm's market, and in turn reduces the idiosyncratic mismatch. Thus, this random increase in aggregate demand is accompanied by a reduction in the firm's idiosyncratic difficulty in finding a customer ε_F , and we can assume that $cov(\lambda, \varepsilon_F)$ is negative and sufficiently large in absolute terms, such that $E[\delta'(t)]$ is always positive.

Aggregate Mismatch, Counter-measures, and Matching Equilibrium

Although we now know about the given mismatch and its decomposition, we have not fully looked at how the match-improving counter-measures by firms and customers affect the mismatch on aggregate. In equation (11) we looked at the partial effect of a firm's countermeasures. To this end we define the aggregate *match-improvement function* $m(t)$ for the aggregate market.

We assume that matching the two market sides is determined by firms' allocation of labor to combat mismatch l_ϕ (see equation 11), and by consumers' purchases of information to improve their search and matching activity θ , and find the desired consumption goods

$$m = L_\phi \theta, \quad \text{with } \frac{dm}{dL_\phi} > 0, \quad \frac{dm}{d\theta} > 0. \quad (17)$$

Thus, the *rate of expected effective aggregate mismatch*, after implementing counter-measures, is

$$E[\delta(t)] = E[\delta'(t)] - m(t). \quad (18)$$

From this discussion we obtain the second equilibrium condition. When the mismatch is completely eliminated by using resources such that the aggregate expected mismatch becomes zero, we obtain a *perfect match* and have a *matching equilibrium*⁹

$$E[\delta(t)] = 0. \quad (19)$$

⁹If this condition holds at the aggregate level, firms are also in sales equilibrium, as they can sell all they produce at the current level of output, such that the *expected effective sales ratio*, individually (13) and on aggregate, turns to 1: $E[\phi(t)] = 1 - E[\delta(t)] = 1$.

2.4 Creation of New Product Ideas and Market Entrance

New Product Ideas In this section we modify equation (2 in Jones 2021) which describes the creation of ideas as $\dot{A} = A^{-\beta_A} R^{\beta_R}$. We assume $\beta_A = 0$, $\beta_R = 1$, and, as equation (5 in Jones 2021), we suppose that R is exogenously determined by the given share \bar{l}_R of the labor force allocated to the firms' R&D activities. Further, we assume that the number of new product ideas $\dot{A}(t)$ is determined by labor in R&D activities and the number of existing technologies in the markets. Firms' new product developments depart from their successfully established products $N(t)$

$$\dot{A}(t) = N(t) \bar{l}_R L. \quad (20)$$

That is, potential technology growth is described by new product ideas that can be produced with existing labor and thus describes a capacity expansion through new products.¹⁰ Note that there is a difference between new product ideas $\dot{A}(t)$ (potential technology growth) that are suggested to the market and new products that are successfully established in the market $\dot{N}(t)$. Only ideas that become successfully established in the market as new products contribute to an economy's effective technology.

Market Entry and Matching New Ideas to Market Demand New product ideas are not automatically fully absorbed by the market. Entrepreneurs¹¹ take up these ideas and go through a market entry process to find customers who are willing to buy these new goods. This market entry process is a second matching process that is described by the aggregate matching function¹²

$$\dot{N}(t) = (E[\lambda(t)])^\gamma v^{1-\gamma} \dot{A}(t). \quad (21)$$

In this matching process, the first component for a successful market entry is the

¹⁰More sophisticated modeling would directly lead to a full model of differentiated goods or the Romer model of growth if this process were described for intermediate goods. However, as in Jones (2021), we merely want to describe a simple stylized mechanism.

¹¹For a micro-foundation of this process, see Gries and Naudé (2011) and Gries et al. (2016).

¹²Again, we borrow from labor market matching approaches when choosing this specification of aggregate matching technologies.

expected excess demand ratio $E[\lambda(t)] = E[Y^D(t)]/Y$. The larger this ratio is, the more demand relative to output is in the market. We suppose that relatively high demand makes it easier to launch new products on the market. The second component is the level of market entry investments v , which indicates the effort per unit of newly introduced technology goods by firms entering the market with new products (see also 4). The third component of this matching mechanism is the number of goods newly suggested to the market $\dot{A}(t)$, which is the result of innovative ideas. Thus, successful market entry is determined by a match between newly supplied goods and the demand that must absorb these goods. We assume that excess demand facilitates the market entry of new goods while a lack of demand is an obstacle to market entry. Note also that in market equilibrium ($\lambda = 1$) we are back to standard endogenous innovation modeling.

2.5 Solving the Model

We can now summarize the model using the two equations (22) and (23) that determine the equilibrium and the path level of the economy.

Labor Allocation and Aggregate Goods Market Equilibrium Aggregate market equilibrium can be determined by using goods market equilibrium condition (9) and plugging in (7), (4), and (20) [see appendix C]. This procedure directly leads to the equilibrium allocation of labor to production¹³

$$l_Y = \frac{v}{(1-c-\theta)(1-g)} \bar{l}_R, \quad \text{with} \quad \frac{dl_Y}{d\theta} > 0, \quad \frac{dl_Y}{dg} > 0. \quad (22)$$

Equation (22) describes combinations of labor in production l_Y and spending on information θ for search and matching by consumers that allow for goods market equilibrium.

Aggregate No-mismatch Equilibrium We now have to determine the labor allocation that leads to the no-mismatch equilibrium. Equation (18), (16), (17) and the no-mismatch equilibrium conditions 19) give

$$E[\delta] = (1 - E[\lambda]) E[\varepsilon_F] - cov(\lambda, \varepsilon_F) - l_\phi \theta = 0.$$

¹³With $\frac{dl_Y}{d\theta} = \frac{v\bar{l}_R}{[(1-c-\theta)(1-g)]^2} (1-g) > 0$ and $\frac{d^2l_Y}{d\theta^2} = \frac{v\bar{l}_R}{[(1-c-\theta)(1-g)]^4} (1-g)^2 > 0$.

As in goods market equilibrium, condition (9) holds and $(1 - E[\lambda]) E[\varepsilon_F]$ turns to zero, and we obtain combinations of firms' labor input in the matching process and consumers' purchases of information goods θ that eliminate the mismatch: $0 = -cov(\lambda, \varepsilon_F) - l_\phi \theta$. Using the labor constraint, we can rewrite this condition and obtain combinations of l_Y and θ that lead to the no-mismatch equilibrium

$$l_Y = 1 - \bar{l}_R + cov(\lambda, \varepsilon_F) \theta^{-1}. \quad (23)$$

Solve for the Level of the Growth Path Using the two equations (22) and (23) we can now determine the equilibrium labor share in production and thus solve for the path level of the economy

$$l_Y^* = \frac{1}{2} \left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + (B-1) \bar{l}_R \pm \left[\left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + (B-1) \bar{l}_R \right]^2 - 4B(1-\bar{l}_R) \bar{l}_R \right]^{\frac{1}{2}} \right], \quad \text{with } \frac{dl_Y^*}{dg} > 0 \quad (24)$$

where $B = \frac{v}{(1-c)(1-g)}$. For a positive solution, we assume that B is sufficiently large. In the Appendix C we present the calculations used to find this solution and determine the derivative. With this allocation of labor in production l_Y^* , the economy produces according to (1)

$$Y^*(t) = N(t) l_Y^* \quad \text{with } \frac{dY^*}{dg} > 0. \quad (25)$$

At this point we see the difference between this model and Jones' (2021) stylized growth model. In Jones' model, as in standard models, the adjustments and reallocations do not require any resource input. In our model, we have a matching problem, adjustments are done through the use of labor and labor reallocation, and they are permanently required. Our point is that in an economy with frictions and mismatch, growth equilibrium includes labor and resources that are allocated to solve the information search and mismatch problem. This labor allocation is a continuous part of the adjustment toward equilibrium, even in the long term.

Note that the aggregate market equilibrium (25) determines the level of the growth path. From the general growth equation $[Y^*(t) = N(0) e^{tg_N} l_Y^*]$ we obtain, for the initial period,

$$Y^*(0) = N(0) L_Y^*, \quad \frac{dY^*(0)}{dg} > 0. \quad (26)$$

Growth Rate The growth rate is determined by the second matching process in section 2.4, which describes the market entry of new products. The growth rate is calculated using (20), (21), and (9). From $Y^*(t) = N(t) L_Y^*$ we also know that $Y(t)$ will grow at the growth rate g_N , and thus in goods market equilibrium

$$g_{Y^*} = g_N = v^{1-\gamma} \bar{l}_R L. \quad (27)$$

That is, for an equilibrium path in which the expected excess demand ratio is $E[\lambda(t)] = 1$, the technology and GDP growth rate is determined by the growth rate of new technologies $g_{Y^*} = g_N = v^{1-\gamma} \frac{\dot{A}(t)}{A(t)}$, similar to standard endogenous growth models.

2.6 Implication for the Growth Process and TFP

Using the identity $Y^*(t) = \frac{Y^*(t)}{Y^P(t)} Y^P(t)$, with potential production $Y^P(t) = N(t)L$, we can define $\Delta^Y(t)$ as the *match efficiency rate*

$$\Delta^Y(t) = \frac{Y^*(t)}{Y^P(t)} \quad \text{with } 0 < \Delta^Y(t) \leq 1 \quad (28)$$

The match efficiency rate describes the ratio of current to potential equilibrium income. According to the model, the rate indicates how many resources have to be allocated to the match-improving processes rather than being used in the production process. The higher this rate is, the fewer resources are required in the matching process and the closer $\Delta^Y(t)$ is to 1. By identifying the match efficiency rate we can rewrite the output equation (1) and again obtain the components of the growth path of the economy, including the effect of potential mismatch

$$Y^*(t) = \underbrace{\Delta^Y(t) N(t)}_{\text{TFP}} \underbrace{L(t)}_{\text{contribution of inputs}}. \quad (29)$$

This equation takes us back to standard growth accounting equations. As suggested by equation (A3) and Section 3 in Jones (2021), we identify his misallocation

term $M = \Delta^Y(t)$ as contributing to TFP in our growth with mismatch model. However, we explicitly label this term as the "match efficiency rate". We can do so since this term is the result of the matching mechanism described in the model. The better the matching, the higher the match efficiency that is an element of TFP. As Y^* and thus Δ^Y are determined using various variables, including the rate of government expenditure g , demand-side elements also matter for the growth path. Thus, in contrast to Jones' (2021) definition of misallocation, we argue in favor of a *persistent* non-vanishing mismatch over time. Firms and customers continually have to search for and acquire information to find market matches. While misallocation refers to the non-optimal use of resources by firms imposed by supply-side market frictions, mismatch in this model requires the use of resources that are not independent of the demand side. Higher aggregate demand increases the match efficiency $\Delta^Y(t)$, the mismatch decreases, and more resources, i.e., labor, can be employed in production. Hence, we have derived a growth model with imperfect market match in which the demand side is included in the TFP term via a matching procedure. Further, the match efficiency rate as an important determinant of TFP can be used for empirical estimates.

$$TFP = \Delta^Y(t) N(t), \quad \frac{dTFP}{d\Delta^Y} > 0 \quad (30)$$

Further, (29) also suggests that TFP growth is determined by changes in the match efficiency rate and technology growth in the economy¹⁴

$$\frac{dTFP}{TFP} = \frac{d\Delta^Y(t)}{\Delta^Y(t)} + \frac{dN}{N}. \quad (31)$$

3 Empirical Identification of Mismatch

Having theoretically concluded that the long-term growth path of an economy is affected by mismatch, we want to empirically test this central hypothesis. Our starting points are equations (30) and (31), which depict the direct relationship between match efficiency and TFP.

If mismatch indeed affects TFP and thus economic growth in the long term, as proposed by the growth with mismatch model, we expect $\Delta^Y(t)$ to have a significant

¹⁴Note that for the equilibrium growth path the growth rate of N is directly driven by the growth rate of the new technology ideas $\frac{\dot{A}}{A}$.

effect on TFP. Technically, we analyze the effect of $\Delta^Y(t)$ on productivity in a panel regression analysis involving 15 developed countries in recent decades up to 2019.¹⁵ The analysis is conducted in *R* using the *fixest* and *plm* packages (see Bergé 2018 and Croissant and Millo 2018, respectively).

Besides the match efficiency rate, which indicates the impact of the matching process on TFP, other potentially TFP-affecting control variables are introduced into the panel analysis. In theory, these control variables reflect factors that represent technology N in TFP determining equations (30) and (31). To introduce these explanatory variables alongside $\Delta^Y(t)$, we build upon the recent approach suggested by Kim and Loayza (2019), who identify five key drivers of TFP, namely *market efficiency*, *education*, *innovation*, *institutions*, and *infrastructure*.

Before conducting our empirical analysis in Section 3.2, we discuss our selected variables in the next Section 3.1. There, we assign our variables to each of these five TFP key drivers such that TFP is extensively examined. A descriptive overview of all variables used in the empirical analysis is provided in Table Table A1 in the Appendix.

3.1 Variables and Data Selection

The dependent variable in our panel analysis is **TFP**. Measuring TFP is a challenging task and estimation results may be unreliable when only one source of TFP data is used. A unique and unambiguous TFP index does not exist. To account for this problem, and for further empirical robustness, we use two independent productivity indices. One set of TFP index data is obtained from the Penn World Table (*PWT-TFP*, see PWT 2021 and Feenstra et al. 2015). A second set is gathered from Banque de France (*BdF-TFP*, see BdF 2021 and Bergeaud et al. 2016). Kim and Loayza (2019) already use PWT-TFP. The selected indices in particular differ in terms of their assumptions about human capital. While it is part of the index calculation for PWT-TFP, that is not true for BdF-TFP. In turn, both indices may differ sharply for single cross sections of data. Evidently, PWT-TFP has a variance about twice as large as BdF-TFP (see *Table A1 (Ref.)*). The larger variance in PWT data can

¹⁵The following countries were included in the analysis: Australia, Austria, Belgium, Canada, Germany, Denmark, Finland, France, Italy, Japan, the Netherlands, Norway, Sweden, the United Kingdom, and the United States. Initially, our data sample for the period 1985 to 2019 contained a lack of data points below 3% of overall data. To resolve this issue, we imputed this data using the *imputeTS* package in *R* (Moritz and Bartz-Beielstein 2017).

be explained by country-specific differences in estimated TFP. For example, in the case of Germany, TFP starts at a lower level according to PWT data and catches up to BdF data after the country's reunification in 1990. By contrast, higher variance in PWT-TFP for Greece is due to the influence of the Financial and European debt crisis post-2007. Unlike in the German case, PWT-TFP for Greece starts at a much higher level but then contracts sharply after 2007. However, given the example of the US, both TFP indices in fact move uniformly.

The TFP key driver of *market efficiency* is represented by the **match efficiency rate**. Given that we focus on mismatch affecting economic growth, this rate also represents our target TFP explanatory variable of interest. It directly refers to our model in Section 2. Mismatch in the aggregate goods market may reduce aggregate output and thus TFP and growth. For the purpose of estimation, we need an empirical measure for the match efficiency rate. Following Orphanides and van Norden (2002), who define the aggregate output gap (OG) as the absolute deviation of actual production from its potential, i.e., $OG = Y^*(t) - Y^P(t)$ with $Y^*(t) \leq Y^P(t)$, we use this definition and define the relative output gap as

$$ROP = \frac{Y^*(t) - Y^P(t)}{Y^P(t)}. \quad (32)$$

Further, departing from definition (28) $\Delta^Y(t) = \frac{Y^*(t)}{Y^P(t)} \in [0, 1]$, we can rewrite¹⁶ and include the relative output gap as a central part to measure the match efficiency rate

$$\Delta^Y(t) = ROP + 1. \quad (33)$$

If $\Delta^Y(t)$ is low, many resources are allocated to the matching process, and so the mismatch is high and the initial match in the markets (match before allocating resources to matching activity) is low. If this ratio is high, resource requirements for the matching process are low and the initial match in the markets is high. Ideally, this ratio is equal to 1, such that no resources are used in the matching process and current output equals potential output. The match efficiency rate therefore indicates how many resources are left in the final production (and how many resources are lost

¹⁶We can write $\frac{Y^*(t)}{Y^P(t)} = \frac{Y^*(t)}{Y^P(t)} - \frac{Y^P(t)}{Y^P(t)} + 1$. Using the definition $\Delta^Y(t) = \frac{Y^*(t)}{Y^P(t)}$ and with the definition of the ROG we arrive at (33).

in the matching mechanism) after solving the mismatch problem.

Given the derived match efficiency rate $\Delta^Y(t)$, with the relative output gap as the central ingredient, we ought to find empirically that this variable makes a significant contribution to both TFP indices. This relationship is central to our empirical analysis. If we were to find a significant effect, this would be evidence that mismatch does indeed affect the growth path such that growth is systematically below its potential level. Only a few studies have so far used the output gap as a potential efficiency driver of TFP. Kataryniuk and Martínez-Martín (2019), for instance, find a robust correlation between the output gap and TFP in emerging economies. Aschauer (1989) detects a positive relationship between the output gap (referred to there as the capacity utilization rate) and overall productivity in the US between 1949 and 1985. Our selected output gap data is gathered from the International Monetary Fund (IMF 2021a) and follows the definition given in equation (33).

While the match efficiency rate is the most important variable, we have to control for further drivers of TFP, again guided by Kim and Loayza (2019).

The second key driver to explaining TFP *education* is proxied by **human capital**. Both Barro (2001) and Hanushek and Woessmann (2015) underline the need for education both in terms of quantity and quality when it comes to overall productivity. For instance, Benhabib and Spiegel (2005) show that an increase in average years of schooling in the second half of the 20th century in many economies can be viewed as a reasonable factor for increasing TFP by means of catching up to the technology frontier. More recently, Jajri (2007), Álvarez-Ayuso et al. (2011) and Gehringer et al. (2016), among others, support this view by providing additional evidence that productivity is positively affected by education. A standard approach to measuring education is to use the average number of completed years of schooling of a population (see, e.g., Barro and Lee 2013, Cohen and Soto 2007, and Cohen and Leker 2014). However, in addition to an indicator that only represents years of schooling, PWT (2021) constructs a complete human capital index that also incorporates return to education. Even though measurements of human capital are always susceptible to measurement error, we argue in favor of the PWT (2021) human capital index, since it relies on a number of measures, incorporates a broad range of countries, and shows high data frequency.

The third driver *innovation* describes the creation and adoption of new technologies. Since innovation is a very broad concept and cannot be reduced to one simple

indicator, we assign three variables to this key driver, namely **R&D**, number of **researchers** in an economy, and number of registered **triadic patent families**. In this regard, we are in broad agreement with Kim and Loayza (2019), who also use R&D and patent measures. While R&D data is the most standard proxy for innovation, the number of triadic patent families also incorporates innovative processes that are not part of the official research effort. Moreover, we include the number of researchers in our estimation since it roughly corresponds to \bar{l}_R in our growth with mismatch model (see Section 2.4), which depicts the share of labor allocated to R&D in private firms. We collect innovation data from the Organisation for Economic Co-operation and Development (OECD). While R&D data is measured as domestic spending as a percentage of GDP (OECD 2021a), the number of researchers is measured per 1,000 people employed (OECD 2021b). The number of triadic patent families registered in an economy as gathered from OECD (2021c) is measured in absolute terms. In our empirical analysis, we scale the number of triadic patent families to be measured in 10,000. The current literature dealing with innovation and TFP especially focusses on particular fields of innovation and their effects. Jorgensen et al. (2008) and Oliner et al. (2008), among others, find that information and communication technologies (ICT) were a central driver of US productivity in the 1990s and 2000s. Van Ark et al. (2008) show that a productivity decline in Europe in the same period can be attributed to lower ICT affinity. Examples of more recent general empirical contributions are Park (2010), Hwang and Wang (2012), Harris and Moffat (2015), Bloom et al. (2020), and Branco et al. (2018).

The fourth driver *institutions* increases productivity by establishing and enforcing market efficiency and sets a framework of social infrastructures within which economic action takes place (Hall and Jones 1999). Referring to OECD countries, Ghali (1999) finds a positive relationship between government spending and TFP. That said, Dar and Amir-Khalkhali (2002) stress that large government size weakens overall TFP by inducing crowding-out effects and distorting market mechanisms by means of taxation and regulation. Institutional quality, like human capital measuring the driver of education, is difficult to examine. Yet, several empirical studies, such as Olomola and Osinubi (2018) concerning Mexico, Indonesia, Nigeria, and Turkey, refer to indices such as the International Country Risk Guide or the Government Anti-Diversionary Policy Index. We follow Kim and Loayza (2019) and refer to the World Bank’s Worldwide Government Indicators (WGI 2021; see Kaufmann et al. 2010).

Specifically, due to our focus on advanced economies, we concentrate on **government effectiveness** and **regulatory quality** to fit with the line of argumentation used by Hall and Jones (1999). Government effectiveness captures "perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures" (Kaufmann et al. 2010: 4), while regulatory quality refers to a government's ability to implement specific regulatory policies.

The fifth TFP key driver *infrastructure* has so far attracted the least attention in the literature. Contributions referring to the relationship between infrastructure and TFP are mostly related to studies dealing with developing and emerging economies which, for example, consider the availability of water supply (see, e.g., Cole and Neumayer 2006 or Danquah et al. 2013). The variables selected by Kim and Loayza (2019) follow the same logic. Besides water supply, they add the length of paved roads and electricity production. The influence of infrastructure has so far largely gone unnoticed in relation to advanced economies. Aschauer (1989) finds evidence for a positive relationship between infrastructure and TFP for the US between 1949 and 1985, but arbitrarily distinguishes between core infrastructure, hospitals, and educational buildings. Álvarez-Ayuso et al. (2011) also find such a positive effect for several European countries using data on public infrastructure investment. Following the latter, we use a very similar approach in our analysis. We use data on **government capital stock** measured in 100 billions of constant 2017 international US dollars (see IMF 2021b). We take the cumulative capital stock instead of investment flows as a suitable variable to reflect infrastructure, since it does not immediately add to the capital stock and is dependent on day-to-day politics.

3.2 Panel Regression and Endogeneity Concerns

In Section 3.1, eight variables are selected to empirically explain TFP and thus long-term growth. Thus, in order to analyze their contributions to the *PWT-TFP* and *BdF-TFP* indices, all five TFP key drivers according to Kim and Loayza (2019) are represented. Given the theoretical linkage between TFP and match efficiency according to equations (30) and (31), we look at both levels and growth rates. This leads to the following two panel regression equations:

$$\begin{aligned}
TFP_{it} = & \phi_0 + \phi_1 \text{match efficiency rate}_{it} \\
& + \phi_2 \text{human_capital}_{it} + \phi_3 \text{R\&D}_{it} \\
& + \phi_4 \text{researchers}_{it} + \phi_5 \text{triadic_patent_families}_{it} \\
& + \phi_6 \text{government_effectiveness}_{it} \\
& + \phi_7 \text{regulatory_quality}_{it} + \phi_8 \text{government_capital_stock}_{it} + \varepsilon_{it},
\end{aligned} \tag{34}$$

$$\begin{aligned}
\frac{dTFP_{it}}{TFP_{it}} = & \phi_0 + \phi_1 \frac{d\text{match efficiency rate}_{it}}{\text{match efficiency rate}_{it}} + \phi_2 \text{match efficiency rate}_{it} \\
& + \phi_3 \text{human_capital}_{it} + \phi_4 \text{R\&D}_{it} \\
& + \phi_5 \text{researchers}_{it} + \phi_6 \text{triadic_patent_families}_{it} \\
& + \phi_7 \text{government_effectiveness} + \phi_8 \text{regulatory_quality} \\
& + \phi_9 \text{government_capital_stock}_{it} + \varepsilon_{it},
\end{aligned} \tag{35}$$

where the first model (34) corresponds to the theoretical consideration of equation (30) and model (35) corresponds to equation (31) in theory.¹⁷ Subscripts i and t refer to countries and time, respectively. The regression analysis was conducted in R using the *fixest* and *plm* packages (see Bergé 2018 and Croissant and Millo 2018, respectively). Estimation results for TFP in levels according to equation 34 are reported in Table 1. Those for TFP in growth rates according to equation 35 are reported in Table 2. Four models are reported in each table, with models (1) to (2) based on the full period from 1985 to 2019. However, *government effectiveness* and *regulatory quality* (obtained from the WGI 2021) are not available for 1985 to 1996, hence they cannot be included in these estimations. Including these variables in models (3) to (4) considerably shortens the observation period to 1996 to 2019.

We conduct Hausman tests for model specification. As a result, country fixed-effect estimators are applied in all selected models. To check for robustness we also introduce models with additional time-fixed effects presented in Table A2 and Table A3 in the Appendix. Since the output gap, and thus the match efficiency rate, behaves cyclically over time, introducing time-fixed effects filters out much of the variability. In this sense, the influence of the output gap on TFP becomes less pronounced (in other words: underestimated). However, as depicted in the Appendix, the match

¹⁷The fact that model 35 contains the match efficiency rate in its growth rate as well as in its level is justified by derivation in the Appendix. The incorporation of the other explanatory variables in levels is also derived there.

efficiency rate remains a significant contributor to TFP even when time-fixed effects are introduced. Heteroscedasticity and autocorrelation are present in the data set, as shown by conducted Breusch-Godfrey-Wooldridge- and Breusch-Pagan tests. In consequence, we apply robust Discroll and Kraay standard errors to adequately account for these attributes.

[Insert Table 1 and Table 2 here]

Models (3) and (4) in Table 1 and Table 2, as well as the models using additional time-fixed affects in the Appendix, use a panel two stage least squares (TSLS) approach instead of the usual ordinary least squares (OLS). The justification for applying this method is directly inferred from our theoretical growth with mismatch model. Endogeneity of the match efficiency rate $\Delta^Y(t)$ becomes a potential concern according to Section 2. Aggregate demand Y^D , as defined in equation (7), determines the current equilibrium production $Y^*(t)$, the relative output gap according to (33), and, ultimately, the match efficiency rate $\Delta^Y(t)$. This, in turn, enhances TFP due to decreasing market mismatch. Nevertheless, TFP is not only affected by changes in $Y^*(t)$, or changes in its demand components, respectively. Reversed causality might also go from TFP to current equilibrium production. Given a change in TFP, actual equilibrium production $Y^*(t)$ changes relative to potential production $Y^P(t)$, such that the match efficiency rate $\Delta^Y(t)$ itself alters. In this constellation of simultaneous causality between TFP and $\Delta^Y(t)$, the correlation between the latter and the error term cannot be ruled out with any certainty. Empirically, this concern is underlined by conducted Wu-Hausman tests. In all TSLS estimations there is the concern that the match efficiency rate $\Delta^Y(t)$ is an endogenous regressor, such that an instrumental variable approach is indeed justified.

The selection of suitable instrumental variables obeys relevance and exogeneity criteria. In models (3) and (4) for TFP in level specification (see Table 1), government expenditure and household consumption are selected as instrumental variables for the potential endogenous match indicator.¹⁸ Moreover, the use of government expenditure as an instrumental variable follows our theoretical variable g . For the TSLS regression models in growth rate specification (see Table 2), we select three

¹⁸The data sources and the measurements of the instrumental variables used can also be found in Table A1 in the Appendix. Too much data is missing to run a reliable imputation for government expenditure in the United States. Instead, White House (2021) data is used as a substitute for US government expenditure.

instruments: household consumption growth, government expenditure growth, and investment. The selected instruments prove strong in weak instruments tests. That is, according to the reported p values, all TSLS models offer suitably large information content in the selected instruments. Moreover, as all TSLS models depicted in Table 1 and Table 2 are overidentified, we can test for instrument exogeneity using Sargan (overidentifying restrictions) tests. The null hypothesis of instrument exogeneity cannot be rejected for any of the listed regression models.

3.3 Estimation Results

We receive significant estimation results for variables reflecting all five key drivers of TFP, that is education, innovation, market efficiency, institutions, and infrastructure. That said, all five key drivers of TFP named in Kim and Loayza (2019) significantly contribute to explaining productivity in our sample of 15 advanced economies. With respect to the match efficiency rate, the estimation results are robust when it comes to the use of the two independent productivity indices, namely PWT-TFP and BdF-TFP. The panel regression results in Table 1 and Table 2 show estimation results in line with our theoretical model. One key result is that we always find a significant influence of the match efficiency rate on TFP in levels as well as in growth rates. In turn, since the match efficiency rate (and the output gap) is affected by demand-side elements, we find implicit evidence that the demand side does affect long-term growth via market mismatch, as proposed in our growth with mismatch model. In the following, we review the parameter estimates for each TFP key driver individually.

Market efficiency: As mentioned in the above, the key result of our instrumental variable panel approach is that the match efficiency rate $\Delta^Y(t)$ has a positive significant effect on TFP. As suggested, an increase in the match efficiency rate and the output gap, respectively, increases the TFP level. According to the regression models in Table 1, a 1% increase in the match efficiency rate increases estimated TFP between 0.0037 and 0.0167 units. In growth rate specification (see Table 2), we also identify a significant impact of mismatch on TFP and economic growth. The TFP growth rate is affected by the growth rate of the match efficiency rate as well as by its level. While the growth rate of the match efficiency rate positively affects TFP growth, its level contributes negatively. This positive effect is in line with our hypothesis in (31). The negative level effect on TFP growth indicates another interesting

mechanism: As soon as output comes closer to potential output, the improvement for TFP through match efficiency declines. In other words, there are fewer and fewer inefficiencies left to be enhanced, such that the contributions of mismatch to TFP decline with improving match efficiency.

Education: Proxied by human capital, we find, as expected, overall positive and significant results for PWT-TFP and BdF-TFP in level specification (see Table 1). That said, in TFP growth rate specification according to Table 2, the estimates for human capital become negative. However, the negative impact of human capital on TFP growth is in line with Jones (2021), who argues that the impact of education on productivity diminishes in advanced economies. Given an already high level of human capital, a further increase will affect TFP growth to a lesser degree.

Innovation: The influence of R&D on TFP is ambiguous. In level specification, we identify a significant positive influence on TFP. In the regressions with TFP growth rate specification, R&D becomes insignificant. R&D becomes a negligible factor in explaining TFP growth rates, again in line with Jones (2021). However, the second and third variable for innovation, namely the number of researchers and the number of triadic patent families, gives clear results for TFP in both levels and growth rates. The parameter estimates are virtually all positive and mostly significant in a statistical sense. The most important and consistently significant variable depicting innovation is the number of researchers. This is also consistent with our theoretical growth with mismatch model (see 27).

Institutions: TFP is positively affected by government effectiveness and regulatory quality in the level specification. However, the effects are limited in both models (3) and (4) in Table 1. The same holds for TFP growth (see Table 2). We conclude that in our sample of advanced economies TFP growth is not primarily driven by institutions.

Infrastructure: Captured by the government capital stock, infrastructure has a positive influence in explaining TFP levels but negatively affects TFP growth rates in our sample. The estimated coefficients are nevertheless always statistically significant. As regards TFP in levels, we therefore find support for the hypothesis that infrastructure is indeed positively related to TFP (see Aschauer 1989 and Álvarez-Ayuso et al. 2011). However, estimates of TFP growth conclude that it becomes more difficult to achieve such growth by further increasing the level of infrastructure.

To conclude, in our sample of 15 advanced economies, TFP is affected by all five

key drivers named by Kim and Loayza (2019). However, given our theoretical model, we especially highlight the influence of the match efficiency rate reflecting market mismatch. Moreover, as mentioned by Jones (2021), and confirmed in our findings, the number of researchers always positively affects TFP and TFP growth.

4 Conclusion

This paper connects market mismatch to economic growth in (i) a theoretical growth model and (ii) an empirical estimation. Departing from the stylized endogenous growth model of Jones (2021), we also include market mismatch and allocative inefficiency. In our model, a market match requires search activities and active resource use on both the supply and the demand side. As this mismatch depends on demand and supply conditions, even aggregate demand matters in this stylized endogenous growth model for long-term growth. That said, shortages in aggregate demand negatively influence TFP and thus economic growth. In consequence, an economy can permanently grow below its potential long-term path since firms' resources have to be used for market matching instead of production. To our knowledge, this is a novel approach. Thus, unlike existing growth models, market inefficiencies are not only inefficiencies on the supply side. In our model, there is an ongoing matching process requiring resources that is also affected by aggregate demand. Thus, the demand side also matters for long-term growth.

We find evidence for this theoretical idea by empirically testing the hypothesis of market mismatch influencing TFP and economic growth. To do so, we identify the match efficiency rate in the model and measure it through the output gap. In times of high aggregate demand (and thus a small output gap), firms face less mismatch, which in turn positively enhances TFP and TFP growth. We introduce the match efficiency rate as the central regressor in a panel data regression analysis for 15 advanced economies between 1985 and 2019. Further control variables are selected according based on the approach of Kim and Loayza (2019), who identify five key drivers of TFP, namely education, innovation, market efficiency, institutions, and infrastructure. We place a special focus on the potential endogeneity of the match efficiency rate and apply a TSLS approach with suitable instrumental variables. Our empirical analysis provides evidence for our theoretical considerations. We detect a significant impact of the match efficiency rate on TFP and thus economic growth. An increase

in the match efficiency rate positively affects TFP. As the match efficiency rate (i.e., an output gap-based measure) relates to the demand side, this finding implies that growth is not purely driven by the supply side, as in standard growth modeling. The demand side is also a potential factor for economic growth. Furthermore, we find evidence for most of the other key drivers of TFP suggested by Kim and Loayza (2019). The number of researchers in an economy in particular has a positive impact on TFP and growth. This result is also in line with our theoretical model and the stylized growth model suggested by Jones (2021).

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Appendix

A Jones' stylized model of growth

We take the model from Jones (2021) as base model for a growth mechanism. In this economy production (1 in Jones 2021) is done purely by labor L_Y (linear homogenous with labor) and technologies A . Equation (2 in Jones 2021) depict the innovation process, and (3 in Jones 2021) and (5 in Jones 2021) describes the allocation of resources to production and innovations. Equation (5 in Jones 2021) is the exogenous labor growth.

$$Y(t) = A^\sigma L_y(t), \sigma > 0 \quad (1 \text{ in Jones 2021})$$

$$\dot{A} = A^{1-\beta_A} R^{\beta_R}, 0 < \beta_A, \beta_R < 1 \quad (2 \text{ in Jones 2021})$$

$$L(t) = L_y(t) + R(t) \quad (3 \text{ in Jones 2021})$$

$$L(t) = L(0) e^{nt} \quad (4 \text{ in Jones 2021})$$

$$R(t) = \bar{l}_R L(t) \quad (5 \text{ in Jones 2021})$$

When Jones solves this model he obtains for the balanced growth path per capita

$$y(t) = \frac{Y(t)}{L(t)} = (1 - \bar{l}_R) (g_A)^{-\frac{\sigma}{\beta_A}} (\bar{l}_R)^{\sigma \frac{\beta_R}{\beta_A}} (L(t))^{\sigma \frac{\beta_R}{\beta_A}} \quad (8 \text{ in Jones 2021})$$

and with g_x being a general growth rate of a variable x he obtains

$$g_y = \sigma \frac{\beta_R}{\beta_A} n. \quad (9 \text{ in Jones 2021})$$

Depending on the parameters n , σ and β_A the model can turn into another growth procedure. E.g., if there is no population growth $n = 0$, $L(0) = L$ and $\sigma = 1, \beta_A = 0$ the model reduces to a simple version of an endogenous growth process driven by the share of labor in R&D.

$$y = A(1 - \bar{l}_R) L \quad (A1)$$

$$g_y = g_A = (\bar{l}_R L)^{\beta_R} \quad (A2)$$

Further, when Jones (2021) extends his discussion to turn to a growth account-

ing exercise he introduces another important variable, namely $M \leq 1$, which is a misallocation term (12 in Jones 2021). This misallocation term describes a loss of actual output compared to potential GDP if allocation were not perfect and is also introduced in his growth accounting equation

$$d \ln y(t) = \underbrace{(d \ln M(t) + d \ln A(t))}_{\text{Residual: TFP}} + \underbrace{\sum b d \ln X(t)}_{\text{Input factors}}. \quad (\text{A3})$$

For the reasoning in this paper the important point in this equation is the suggestion that TFP growth has two elements. (i) new technologies ($d \ln A$) positively affect total factor productivity, and (ii) improvements of conditions of misallocation ($d \ln M$) may also contribute to total factor productivity. This factor of misallocation is in the focus of this contribution.

B Deriving condition (12) and (13) for the individual firm

As firms cannot sell more than their current output we restrict $E[\phi_i]$ to take values only in the interval $[0, 1]$. Further, above we argued that only $\phi_i Y_i$ of total output can be instantly sold. Thus, expected effective sales are $E[\phi_i] Y$. If a firm allocates labor to the sales process L_{ϕ_i} the marginal effect on effective sales and thus on revenues is $\frac{\partial E[\phi_i]}{\partial L_{\phi_i}} Y_i$. Simultaneously, if a firm allocates labor to real production the marginal effect on effective sales and revenues is $E[\phi_i] \frac{\partial Y_i}{\partial L_{Y_i}}$. Further, we assume for $0 < E[\phi_i] \leq 1$ that the marginal contribution on expected effective sales of a unit L_{ϕ_i} is always larger than the marginal contribution of L_{Y_i} , $\frac{\partial E[\phi_i]}{\partial L_{\phi_i}} Y_i > E[\phi_i] \frac{\partial Y_i}{\partial L_{Y_i}}$. Thus, with $\eta_{E[\phi_i], L_{\phi_i}} = \frac{\partial E[\phi_i]}{\partial L_{\phi_i}} \frac{L_{\phi_i}}{E[\phi_i]}$ and $\eta_{Y_i, L_{Y_i}} = \frac{\partial Y_i}{\partial L_{Y_i}} \frac{L_{Y_i}}{Y_i}$ we obtain condition 12). Consequently, as long as $E[\phi_i] \leq 1$ employing labor to improve the sales ratio is always a higher priority than increasing employment in the production process L_{Y_i} . This procedure implies that the firm will expand L_{ϕ_i} up to $E[\phi_i] = 1$ is reached. Thus, for the employment L_{ϕ_i} there is no inner solution, but we reach a corner solution at $E[\phi_i] = 1$.

C Calculations to section 2.5

C.1 Solving for aggregate goods market equilibrium as determined by l_Y and θ :

Using equilibrium condition (9) and plugging in (7), (4) and (20) gives $1 = E \left[\frac{Y^D(t)}{Y(t)} \right] = \frac{v}{(1-c)(1-g)} \frac{\bar{l}_R L}{l_Y L}$, and rearranging leads to

$$l_Y = \frac{v}{(1-c-\theta)(1-g)} \bar{l}_R.$$

C.2 Solving for no-mismatch equilibrium as determined by l_Y and θ :

We combine the matching equilibrium condition (19) and combine with the labor constraint (2) to obtain (23):

$$\begin{aligned} 0 &= -cov(\lambda, \varepsilon_F) - l_\phi \theta \\ 0 &= -cov(\lambda, \varepsilon_F) \theta^{-1} - (1 - \bar{l}_R - l_Y) \\ l_Y &= 1 - \bar{l}_R + cov(\lambda, \varepsilon_F) \theta^{-1} \\ l_Y \theta &= (1 - \bar{l}_R) \theta + cov(\lambda, \varepsilon_F) \\ -(1 - \bar{l}_R) \theta + l_Y \theta &= +cov(\lambda, \varepsilon_F) \\ -[1 + \bar{l}_R - l_Y] \theta &= +cov(\lambda, \varepsilon_F) \\ \theta &= -\frac{cov(\lambda, \varepsilon_F)}{[1 + \bar{l}_R - l_Y]} \end{aligned}$$

C.3 Find an overall solution: for l_Y :

We use (22) and (23) to solve for l_Y and θ : Rearranging (23) to $\theta = -\frac{cov(\lambda, \varepsilon_F)}{[1 - l_Y - \bar{l}_R]}$ allows to plug in

$$l_Y = \frac{v}{(1-c-\theta)(1-g)} \bar{l}_R$$

Further rearrangements lead to a quadratic equation:

$$\begin{aligned} (1-c)l_Y - \theta l_Y &= \frac{v}{(1-g)}\bar{l}_R \\ (1-c)l_Y + \frac{\text{cov}(\lambda, \varepsilon_F)}{[1-l_Y-\bar{l}_R]}l_Y &= \frac{v}{(1-g)}\bar{l}_R \\ [1-l_Y-\bar{l}_R](1-c)l_Y + \text{cov}(\lambda, \varepsilon_F)l_Y &= [1-l_Y-\bar{l}_R]\frac{v}{(1-g)}\bar{l}_R \end{aligned}$$

$$\begin{aligned} (1-c)l_Y - l_Y(1-c)l_Y - \bar{l}_R(1-c)l_Y + \text{cov}(\lambda, \varepsilon_F)l_Y &= \frac{v}{(1-g)}\bar{l}_R - l_Y\frac{v}{(1-g)}\bar{l}_R - \bar{l}_R\frac{v}{(1-g)}\bar{l}_R \\ l_Y - l_Yl_Y - \bar{l}_Rl_Y + \frac{\text{cov}(\lambda, \varepsilon_F)}{(1-c)}l_Y &= -\frac{v}{(1-c)(1-g)}\bar{l}_Rl_Y + \frac{(1-\bar{l}_R)v}{(1-c)(1-g)}\bar{l}_R \end{aligned}$$

$$\begin{aligned} 0 &= l_Yl_Y - l_Y + \bar{l}_Rl_Y - \frac{\text{cov}(\lambda, \varepsilon_F)}{(1-c)}l_Y - \frac{v}{(1-c)(1-g)}\bar{l}_Rl_Y + \frac{(1-\bar{l}_R)v}{(1-c)(1-g)}\bar{l}_R \\ 0 &= l_Yl_Y - \left[1 + \frac{\text{cov}(\lambda, \varepsilon_F)}{(1-c)} - \left(1 - \frac{v}{(1-c)(1-g)}\right)\bar{l}_R\right]l_Y + \frac{(1-\bar{l}_R)v}{(1-c)(1-g)}\bar{l}_R \\ 0 &= l_Y^2 - \left[1 + \frac{\text{cov}(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1\right)\bar{l}_R\right]l_Y + \frac{(1-\bar{l}_R)v}{(1-c)(1-g)}\bar{l}_R \end{aligned}$$

Defining $b = -\left[1 + \frac{\text{cov}(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1\right)\bar{l}_R\right]$ and $c = \frac{(1-\bar{l}_R)v}{(1-c)(1-g)}\bar{l}_R$ leads to the explicit solution

$$l_Y = \frac{-b \pm [b^2 - 4c]^{\frac{1}{2}}}{2}.$$

or as detailed expression ;

$$l_Y^* = \frac{1 + \frac{\text{cov}(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1\right)\bar{l}_R \pm \left[\left[1 + \frac{\text{cov}(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1\right)\bar{l}_R\right]^2 - 4\frac{(1-\bar{l}_R)v}{(1-c)(1-g)}\bar{l}_R\right]^{\frac{1}{2}}}{2}$$

Show that the solution exists and is positive: However, in the next step we must make sure, that this solution indeed exists and is positive. We show that condition

$$(1-c) \left[1 + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] > -cov(\lambda, \varepsilon_F) \quad (36)$$

is a sufficient condition for a solution to exist and to be positive:

Existence of solution: There is only a solution, if the term $\left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right]^2 - 4 \frac{(1-\bar{l}_R)v}{(1-c)(1-g)} \bar{l}_R > 0$. Thus, we have to find the respective condition:

$$\left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right]^2 - 4 \frac{(1-\bar{l}_R)v}{(1-c)(1-g)} \bar{l}_R > 0$$

$$\left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] \left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] - 4 \frac{(1-\bar{l}_R)v}{(1-c)(1-g)} \bar{l}_R$$

$$\begin{aligned} & 1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \frac{v}{(1-c)(1-g)} \bar{l}_R - \bar{l}_R + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} \left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] \\ & + \frac{v}{(1-c)(1-g)} \bar{l}_R - \bar{l}_R + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left[\left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right]^2 \\ & - 4 \frac{v}{(1-c)(1-g)} \bar{l}_R + 4 \frac{\bar{l}_R v}{(1-c)(1-g)} \bar{l}_R \end{aligned}$$

$$\begin{aligned} & 1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} - \bar{l}_R + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} \left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] \\ & - \bar{l}_R + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left[\left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right]^2 \\ & - 2 \frac{v}{(1-c)(1-g)} \bar{l}_R + 4 \frac{\bar{l}_R v}{(1-c)(1-g)} \bar{l}_R \end{aligned}$$

$$\begin{aligned} & 1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} - 2\bar{l}_R + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} \left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] \\ & + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left[\left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right]^2 \\ & - (1 - 2\bar{l}_R) 2 \frac{v}{(1-c)(1-g)} \bar{l}_R \end{aligned}$$

$$\begin{aligned} & \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} \left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] \\ & + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left[\left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right]^2 \\ & (1 - 2\bar{l}_R) \left[1 - 2 \frac{v}{(1-c)(1-g)} \bar{l}_R \right] \end{aligned}$$

$$\begin{aligned} & \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left[\frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] \\ & + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left[\left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right]^2 \\ & (1 - 2\bar{l}_R) \left[1 - 2 \frac{v}{(1-c)(1-g)} \bar{l}_R \right] \end{aligned}$$

$$\begin{aligned} & \left[\left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right]^2 + \left(\frac{cov(\lambda, \varepsilon_F)}{(1-c)} \right)^2 + 2 \frac{cov(\lambda, \varepsilon_F)}{(1-c)} \left[1 + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] \\ & - (1 - 2\bar{l}_R) \left[2 \frac{v}{(1-c)(1-g)} \bar{l}_R - 1 \right] \end{aligned}$$

Sufficient condition for co-variance terms:

$$\begin{aligned} & \left(\frac{cov(\lambda, \varepsilon_F)}{(1-c)} \right)^2 + 2 \frac{cov(\lambda, \varepsilon_F)}{(1-c)} \left[1 + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] > 0 \\ & 2(1-c) \left[1 + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] > -cov(\lambda, \varepsilon_F). \end{aligned}$$

assuming condition (36) to hold, this condition also holds.

Sufficient condition for non co-variance terms:

$$\begin{aligned} & \left[\left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right]^2 - (1 - 2\bar{l}_R) \left[2 \frac{v}{(1-c)(1-g)} \bar{l}_R - 1 \right] > 0 \\ & \left[\left(\frac{v}{(1-c)(1-g)} \bar{l}_R - \bar{l}_R \right) \left(\frac{v}{(1-c)(1-g)} \bar{l}_R - \bar{l}_R \right) \right]^2 - (1 - 2\bar{l}_R) \left[2 \frac{v}{(1-c)(1-g)} \bar{l}_R - 1 \right] > 0 \end{aligned}$$

$$\left(\frac{v}{(1-c)(1-g)} \bar{l}_R - \bar{l}_R \right) \left(\frac{v}{(1-c)(1-g)} \bar{l}_R - \bar{l}_R \right) > (1 - 2\bar{l}_R) \left[2 \frac{v}{(1-c)(1-g)} \bar{l}_R - 1 \right]$$

$$\begin{aligned} (A\bar{l}_R - \bar{l}_R) (A\bar{l}_R - \bar{l}_R) - (1 - 2\bar{l}_R) [2A\bar{l}_R - 1] &> 0 \\ (A\bar{l}_R - \bar{l}_R) (A\bar{l}_R - \bar{l}_R) - [2A\bar{l}_R - 1] + 2\bar{l}_R [2A\bar{l}_R - 1] &> 0 \\ A\bar{l}_R (A\bar{l}_R - \bar{l}_R) - \bar{l}_R (A\bar{l}_R - \bar{l}_R) - 2A\bar{l}_R + 1 + 2\bar{l}_R [2A\bar{l}_R - 1] &> 0 \\ A\bar{l}_R A\bar{l}_R - A\bar{l}_R \bar{l}_R - \bar{l}_R A\bar{l}_R + \bar{l}_R \bar{l}_R - 2A\bar{l}_R + 1 + 2\bar{l}_R 2A\bar{l}_R - 2\bar{l}_R &> 0 \\ A\bar{l}_R A\bar{l}_R - 2A\bar{l}_R \bar{l}_R + \bar{l}_R \bar{l}_R - 2A\bar{l}_R + 1 + 4A\bar{l}_R \bar{l}_R - 2\bar{l}_R &> 0 \\ 1 + A\bar{l}_R A\bar{l}_R + \bar{l}_R \bar{l}_R + 2A\bar{l}_R \bar{l}_R - 2A\bar{l}_R - 2\bar{l}_R &> 0 \end{aligned}$$

$$\begin{aligned} \frac{1}{\bar{l}_R} + A\bar{l}_R A + \bar{l}_R &> 2(1 - \bar{l}_R) A + 2 \\ \frac{1}{\bar{l}_R \bar{l}_R} - 1 + \left[\frac{v}{(1-c)(1-g)} - 2 \left(\frac{1 - \bar{l}_R}{\bar{l}_R} \right) \right] A &> 0 \end{aligned}$$

$$\begin{aligned} \frac{v}{(1-c)(1-g)} - 2 \left(\frac{1 - \bar{l}_R}{\bar{l}_R} \right) &> 0 \\ \bar{l}_R v &> 2(1 - \bar{l}_R)(1-c)(1-g) \\ \bar{l}_R v &> 2(1-c)(1-g) - 2\bar{l}_R(1-c)(1-g) \\ \bar{l}_R &> \frac{1}{\left[\frac{v}{2(1-c)(1-g)} + 1 \right]} \end{aligned}$$

Show that there is exists a positive solution: A positive solution exists if

$$1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R > 0,$$

and thus

$$(1-c) \left[1 + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] > -cov(\lambda, \varepsilon_F) > 0$$

In condition (36) we have assumed this condition to hold.

Derivative of l_Y^* with respect to g : We take the derivative step by step:

First term:

$$\frac{d\bar{\Pi}}{dg} = \frac{v\bar{l}_R}{(1-c)(1-g)^2} > 0$$

Second term:

$$\begin{aligned} \frac{d\bar{\Pi}}{dg} &= 2 \left[1 + \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R \right] \frac{v\bar{l}_R}{(1-c)(1-g)^2} - 4 \frac{v\bar{l}_R}{(1-c)(1-g)^2} \\ &= \left[2 + 2 \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + 2 \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R - 4 \right] \frac{v\bar{l}_R}{(1-c)(1-g)^2} \end{aligned}$$

$$2 + 2 \frac{cov(\lambda, \varepsilon_F)}{(1-c)} + 2 \left(\frac{v}{(1-c)(1-g)} - 1 \right) \bar{l}_R - 4 > 0$$

$$\frac{v\bar{l}_R}{(1-c)(1-g)} - \bar{l}_R > -\frac{cov(\lambda, \varepsilon_F)}{(1-c)}$$

$$\left(\frac{v}{(1-g)} - (1-c) \right) \bar{l}_R > -cov(\lambda, \varepsilon_F)$$

$$\frac{v}{(1-g)} - (1-c) > 0$$

$$\frac{v}{(1-g)} > (1-c)$$

As v is not a share but an absolute value spend on an innovation for market entry this condition easily holds. Thus, both terms have a positive derivative with respect to g , and thus,

$$\frac{dl_Y^*}{dg} > 0.$$

D Derivation of empirical model: section 3.2

Starting with 31 we substitute $dN(t)$ using 21 leading to

$$\begin{aligned}\frac{\dot{N}(t)}{N} &= (E[\lambda(t)])^\gamma v^{1-\gamma} \frac{\dot{A}(t)}{N} \\ \frac{\dot{A}(t)}{N(t)} &= \bar{l}_R L\end{aligned}$$

$$\begin{aligned}\frac{dTFP}{TFP} &= \frac{d\Delta^Y(t)}{\Delta^Y(t)} + \frac{dN}{N} \\ &= \frac{d\Delta^Y(t)}{\Delta^Y(t)} + (E[Y^D(t)]/Y)^\gamma v^{1-\gamma} \frac{\dot{A}(t)}{N} \\ &= \frac{d\Delta^Y(t)}{\Delta^Y(t)} + v^{1-\gamma} \bar{l}_R L\end{aligned}$$

$$\frac{dTFP}{TFP} = \frac{d(\Delta^Y(t) + 1)}{(\Delta^Y(t) + 1)} + (\Delta^Y(t))^\gamma \bar{l}_R L v^{1-\gamma}$$

such that the match efficiency indicator $\Delta^Y(t)$ appears in its growth rate as well as in its level on the right-hand side.

Using 21

$$TFP = \Delta^Y(t) N(t), \quad \frac{dTFP}{d\Delta^Y} > 0$$

E Descriptive statistics and further estimation results

Table A1: Descriptive Statistics

variable	mean	variance	available time period	measure	data source
PWT-TFP	0.9530	0.0055	1985-2019	index	PWT (2021)
BdF-TFP	0.9510	0.0024	1985-2019	index	BdF (2021)
output gap	99.7395	4.3482	1985-2019	% of potential GDP	IMF (2021a)
human capital	3.2759	0.0783	1985-2019	index	PWT (2021)
R&D	2.1568	0.4292	1985-2019	% of GDP	OECD (2021a)
researchers	8.1130	11.6098	1985-2019	per 1.000 people employed	OECD (2021b)
triadic patent families	0.2763	0.2230	1985-2019	in 10.000	OECD (2021c)
government expenditure	45.8571	67.2999	1985-2019	% of GDP	IMF (2021a), White House (2021)
household consumption	54.8363	55.7514	1985-2019	% of GDP	PWT (2021)
investment	22.9780	10.2903	1985-2019	% of GDP	IMF (2021a)
government capital stock	16.2100	669.5282	1985-2019	in 100 bn. of 2017 real USD	IMF (2021b)
government effectiveness	1.6767	0.1418	1996-2019	index	WGI (2021)
regulatory quality	1.5047	0.1037	1996-2019	index	WGI (2021)

(Table A1)

Table A2: Panel Regression Results for TFP in Level Specification using additional time fixed effects

	(5)	(6)
	PWT-TFP	BdF-TFP
match efficiency rate	0.0167*** (0.0049)	-0.0056*** (0.0016)
human capital	-0.3528*** (0.0368)	-0.0594*** (0.0111)
R&D	-0.0392*** (0.0073)	-0.0039 (0.0031)
researchers	0.0011 (0.0018)	-0.0004** (0.0005)
triadic patent families	0.0300 (0.0418)	0.0058 (0.0111)
government effectiveness	0.0718*** (0.0209)	0.0249** (0.0105)
regulatory quality	-0.0457*** (0.0134)	-0.0150*** (0.0053)
government capital stock	0.0019** (0.0008)	0.0009*** (0.0003)
Estimation Type	TOLS	TOLS
Instrumental Variables	government. exp., investment growth.	government exp., investment growth.
Fixed Effects	Country, Time	Country, Time
Weak Instrument Test	0.0001	0.0001
Wu Hausman Test	0.0001	0.0055
Sargan Test	0.6219	0.4828
Time Period	1996-2019	1996-2019

Notes: Estimated coefficients, standard errors are depicted in parantheses.

H0 of Weak Instrument Test: weak instruments, H0 of Wu Hausman Test:

absence of endogeneity of instrumented variables, H0 of Sargan Test:

Instruments are not correlated with residuals in the second stage regression

Reported P values are referred to as follows:

* $P(z) < 0.10$, ** $P(z) < 0.05$, *** $P(z) < 0.01$

(Table A2)

Table A3: Panel Regression Results for TFP in Growth Rate Specification using additional time fixed effects

	(5)	(6)
	PWT-TFP	BdF-TFP
match efficiency rate growth	0.3401*** (0.1180)	0.1813*** (0.0478)
match efficiency rate	0.0002 (0.0009)	-0.0005 (0.0005)
human capital	-0.0193 (0.0138)	-0.0067 (0.0062)
R&D	-0.0002 (0.0016)	-0.0003 (0.0009)
researchers	0.0004 (0.0003)	0.0004*** (0.0001)
log(triadic patent families)	0.0102*** (0.0036)	0.0022 (0.0022)
government effectiveness	-0.0023 (0.0058)	-0.0003 (0.0021)
regulatory quality	0.0015 (0.0046)	0.0001 (0.0020)
log(government capital stock)	-0.0192*** (0.0060)	-0.0067** (0.0025)
Estimation Type	TOLS	TOLS
Instrumental Variables	househ. cons. growth, government. exp., investment growth	househ. cons. growth, government. exp., investment growth
Fixed Effects	Country, Time	Country, Time
Weak Instrument Test	0.0001, 0.0001	0.0001, 0.0001
Wu Hausman Test	0.0001	0.0020
Sargan Test	0.6480	0.5404
Time Period	1996-2019	1996-2019

Notes: Estimated coefficients, standard errors are depicted in parantheses.

Diagnostics (Weak Instrument, Wu Hausman, Sargan) defined as in Table A2.

Concerning the Weak Instrument Test, the first value corresponds to the output gap growth variable, the second one to the output gap variable.

Reported P values are referred to as follows: * $P(z) < 0.10$, ** $P(z) < 0.05$, *** $P(z) < 0.01$

(Table A3)

Tables

Table 1: Panel Regression Results for TFP in Level Specification

	(1)	(2)	(3)	(4)
	PWT-TFP	BdF-TFP	PWT-TFP	BdF-TFP
match efficiency rate	0.0074*** (0.0015)	0.0037*** (0.0008)	0.0116*** (0.0022)	0.0051*** (0.0010)
human capital	0.1382*** (0.0266)	0.1784*** (0.0112)	0.0294* (0.0166)	0.1295*** (0.0082)
R&D	0.0216*** (0.0065)	0.0230*** (0.0025)	-0.0092 (0.0072)	0.0113** (0.0045)
researchers	0.0036*** (0.0008)	0.0017*** (0.0005)	0.0055*** (0.0013)	0.0013** (0.0006)
triadic patent families	0.0253** (0.0104)	0.0135** (0.0060)	0.0063 (0.0199)	0.0084 (0.0081)
government effectiveness	—	—	0.0385*** (0.0120)	0.0131 (0.0081)
regulatory quality	—	—	0.0315 (0.0207)	0.0188** (0.0089)
government capital stock	0.0019*** (0.0004)	0.0014*** (0.0002)	0.0038*** (0.0006)	0.0020*** (0.0003)
Estimation Type	OLS	OLS	TOLS	TOLS
Instrumental Variables	—	—	government, exp., household, cons.	government, exp., household, cons.
Fixed Effects	Country	Country	Country	Country
Weak Instrument Test	—	—	0.0001	0.0001
Wu Hausman Test	—	—	0.0001	0.0002
Sargan Test	—	—	0.6520	0.6654
Time Period	1985-2019	1985-2019	1996-2019	1996-2019

Notes: Estimated coefficients, standard errors are depicted in parantheses. H0 of Weak Instrument Test: weak instruments, H0 of Wu Hausman Test: absence of endogeneity of instrumented variables, H0 of Sargan Test: Instruments are not correlated with residuals in the second stage regression. Reported P values are referred to as follows: * $P(z) < 0.10$, ** $P(z) < 0.05$, *** $P(z) < 0.01$

(Table 1)

Table 2: Panel Regression Results for TFP in Growth Rate Specification

	(1)	(2)	(3)	(4)
	PWT-TFP	BdF-TFP	PWT-TFP	BdF-TFP
match efficiency rate growth	0.6465*** (0.0588)	0.3083*** (0.0238)	0.7418*** (0.0664)	0.3239*** (0.0281)
match efficiency rate	-0.0016*** (0.0004)	-0.0007*** (0.0002)	-0.0030*** (0.0007)	-0.0011*** (0.0003)
human capital	-0.0286*** (0.0049)	-0.0162*** (0.0020)	-0.0323*** (0.0106)	-0.0189*** (0.0050)
R&D	-0.0017 (0.0015)	-0.0013 (0.0008)	0.0009 (0.0020)	-0.0010 (0.0006)
researchers	0.0006*** (0.0002)	0.0002** (0.0001)	0.0008** (0.0003)	0.0004*** (0.0001)
log(triadic patent families)	0.0075** (0.0031)	0.0046*** (0.0011)	0.0107*** (0.0031)	0.0036*** (0.0008)
government effectiveness	—	—	-0.0058 (0.0046)	-0.0005 (0.0013)
regulatory quality	—	—	0.0041 (0.0038)	0.0004 (0.0012)
log(government capital stock)	-0.0083* (0.0050)	-0.0048** (0.0020)	-0.0234** (0.0058)	-0.0102*** (0.0028)
Estimation Type	OLS	OLS	TOLS	TOLS
Instrumental Variables	—	—	househ. cons. growth, gov. exp. growth, investment	househ. cons. growth, gov. exp. growth, investment
Fixed Effects	Country	Country	Country	Country
Weak Instrument Test	—	—	0.0001, 0.0001	0.0001, 0.0001
Wu Hausman Test	—	—	0.0006	0.0322
Sargan Test	—	—	0.4793	0.9466
Time Period	1985-2019	1985-2019	1996-2019	1996-2019

Notes: Estimated coefficients, standard errors are depicted in parantheses.

Diagnostics (Weak Instrument, Wu Hausman, Sargan) defined as in Table 1.

Concerning the Weak Instrument Test, the first value corresponds to the match efficiency rate growth variable, the second one to the respective level variable.

Reported P values are referred to as follows: * $P(z) < 0.10$, ** $P(z) < 0.05$, *** $P(z) < 0.01$

(Table 2)