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Competition Policy and Productivity Growth: An Empirical Assessment*

Paolo Buccirossi,[†] Lorenzo Ciari,[‡] Tomaso Duso,[§] Giancarlo Spagnolo,[¶] and Cristiana Vitale[†]

May 17, 2011

Abstract

This paper empirically investigates the effectiveness of competition policy by estimating its impact on Total Factor Productivity (TFP) growth for 22 industries in 12 OECD countries over the period 1995-2005. We find a robust positive and significant effect of competition policy as measured by newly created indexes. We provide several arguments and results based on instrumental variables estimators and non-linearities to support the claim that the established link can be interpreted in a causal way. At a disaggregated level, the effect on TFP growth is particularly strong for specific aspects of competition policy related to its institutional set up and antitrust activities (rather than merger control). The effect is strengthened by good legal systems, suggesting complementarities between competition policy and the efficiency of law enforcement institutions.

Keywords: Competition Policy, Productivity Growth, TFP, Institutions, Deterrence, OECD
JEL classification: L4, K21, O4, C23

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1 Introduction

The aim of this paper is to assess the effectiveness of competition policy in providing higher welfare to society thanks to improved efficiency and productivity.[1] While most economists, starting from Adam Smith, agree that *competition* works in the general interest, there is no such consensus on the ability of *competition policy* to be socially beneficial. Some economists, dating back to the Austrian School (e.g., Von Mises, 1940), argue that any state intervention that interferes with free markets will make society worse off. According to them, competition policy is not an exception, even though its aim is to safeguard effective competition.

More recently, Crandall and Winston (2003) claim that, at least in the US, antitrust law has been ineffective. They maintain that its poor performance is mostly due to the difficulty of distinguishing genuine and healthy competition from anti-competitive behaviors (in all areas of competition law) and to the undervalued power of the markets to curb anti-competitive abuses. They do not ask for a repeal of antitrust law, but urge applying it only for blatant price-fixing and mergers to monopoly. Baker (2003) and Werden (2003) disagree with Crandall and Winston's point of view. They argue that the net effect of competition policy on social welfare is positive. In their opinion, competition policy improves social welfare also (or mostly) by inducing firms to forgo anti-competitive behaviors without the explicit intervention of any competition authority, i.e., by deterring them. The debate appears to be still unsettled. As noted by Whinston (2006), even in the most established area of competition policy, cartel deterrence, 'strong' empirical evidence of the actual effects on social welfare of the practices forbidden by antitrust law (e.g., competitors communicating on prices), and of active antitrust law enforcement on social welfare, is still missing.

This paper is an attempt to provide 'strong' empirical evidence, at least with respect to the effectiveness of the application of competition law in general. In order to do so, we estimate the impact of competition policy and some of its components on total factor productivity (TFP) growth using a sample of 22 industries in 12 OECD countries over the period 1995-2005.

[1] By competition policy we mean the set of prohibitions and obligations that forms the substantive rules of competition (or antitrust) law together with the array of tools available to competition authorities for policing and punishing any violation of the same rules.

To measure competition policy, we identify a set of its institutional and enforcement features that we consider to be key in deterring anti-competitive behaviors. We then aggregate these variables to form a set of summary indicators, the Competition Policy Indicators (CPIs). We generate an Aggregate CPI that summarizes all the key features of the competition policy of a country, as well as more disaggregated ones that refer only to the features of competition policy relative to specific behaviors (i.e., cartels, other competitive agreements and abuses of dominance – collectively referred to as 'antitrust' – and mergers), or only to the 'institutional' or the 'enforcement' features of a competition policy.

As a measure of efficiency we use TFP growth. The theoretical and empirical literature has shown the existence of a positive relationship between competition and productivity. Nickell (1996), Blundell et al. (1999) and Aghion et al. (2004, 2009), using firm-level data, show that product market competition spurs productivity. Aghion and Schankerman (2004) provide a theoretical framework to show that competition-enhancing policies may improve productivity. Based on this literature and other specific reasons, as we will argue in more detail in section 2, we believe that there should be a positive link between good competition policy and TFP growth.

In all specifications of our model, we control for country-industry and time fixed-effects, product market regulation, trade liberalization, and other likely determinants of productivity growth. We find that the Aggregate CPI has a positive and highly significant effect on TFP growth. This impact is larger for industries farther away from the technological frontier, suggesting that effective competition in such laggard sectors is even more important to foster productivity and increase efficiency. When we use the more disaggregated CPIs, which allow us to separate the effects of the institutional and enforcement features, and to distinguish between mergers and antitrust, we find positive and significant coefficient estimates for all these indicators, though institutions and antitrust appear to have the strongest and a more significant impact on productivity growth. For the Aggregate CPI we find the same result both when we estimate the model by OLS, as well as in alternative IV specifications, which use political variables as instruments for the policy.

In addition to the IV estimation, we exploit the possible non-linearities in the effectiveness of competition policy on productivity growth to improve our identification strategy. Competition policy is indeed embedded in a wider and interconnected system of institutions and policies that might present inherent complementarities (Aghion and Howitt, 2006). In our context, legal institutions stand out as particularly relevant, since the enforcement of competition law is intimately linked to the functioning of the judiciary. As expected, we find that competition policy is more effective in countries with better legal institutions, as well as in industries where no other sector-specific authorities are in charge of regulating the competitive processes.

The interaction between competition policy and institutions is not only part of our identification strategy but it is an important point by itself.[2] Indeed, competition policy does not work in isolation. Our CPIs describe some *internal* features of competition policy. However, the effectiveness of competition policy is also likely to depend on *external* factors: the quality of a country's institutions in general, and of its judicial system, in particular. These external factors may matter for two main reasons. First, the general quality of the institutions of a country creates an environment that affects the effectiveness of all public policies. In a context where public bodies in general are effective and efficient the bodies that preside over the enforcement of competition law also tend to be effective and efficient. Hence, if we do not control for institutions, the CPIs might capture some features that, instead, are a reflection of these more general factors. Second, as already pointed out, inherent complementarities between competition policy and the judicial system might exist. For these reasons the courts, and the legal system in general, may play an important role in determining the deterrence properties of a competition policy regime. When we add the dimension of the quality of the institutions to our estimate, we observe that there are both direct effects of institutions on TFP growth and complementarities between them and our measures of competition policy. Indeed, we find that the effects of com-

[2]The interaction between a country's legal rules and economic activities has recently attracted a large interest following the path-breaking work by La Porta et al. (1997, 1998). It has been shown that legal origins affect many dimensions including bank ownership (La Porta et al. 2002), entry regulations (Djankov et al. 2002), labor market regulation (Botero et al. 2004), and government ownership of the media (Djankov et al. 2003a). Some studies also looked at how the characteristics of the judiciary and other government institutions affect the security of property rights and contract enforcement (Djankov et al., 2003b; La Porta et al., 2008). On the basis of the results by Djankov et al. (2003a) and La Porta et al. (2004) we expect that a lower level of formalism of the judicial procedures and greater judicial independence should improve the quality of the judicial review of the decisions made by competition authorities. Hence, we expect positive complementarities between several indicators of the quality of the judiciary system and competition policy. Recently, Malmendier (2009) critically discusses the literature on the nexus between law, finance, and growth. The debate is still unsettled and it is not the aim of this paper to enter it.

petition policy are strengthened in countries where the cost of enforcing contracts are low and the quality of the legal system is high, which points to sizable institutional complementarities between competition policy and the efficiency of legal institutions.

Our paper contributes to the still very limited empirical literature that evaluates the effectiveness of competition policy. Dutz and Hairy (1999) and Dutz and Vagliasindi (2000) use a cross-section of 52 countries and a small sample of transition economies respectively and find a positive effect of antitrust effectiveness on GDP growth. However, they use 'subjective' measures of competition policy that are based on the perceptions of market participants, which, as a consequence, may not correctly represent the objective features of a competition policy regime. Konings et al. (2001) and Kee and Hoekmann (2007) look at the impact of the introduction of competition policy on industrial mark-ups in two very different samples (the first one includes Belgium and the Netherlands and the second includes a large panel of industries in developed and developing countries). Neither paper finds direct evidence of a positive effect of the introduction of competition policy or competition law on mark-ups.[3] However, the interpretation of the results might be misleading as the employed measure of competition policy appears inadequate to capture those features that are likely to impact on its effectiveness.

Our work is also closely related to the literature that examines the impact of regulation and other competition-enhancing policies on productivity growth. Nicoletti and Scarpetta (2003) focus on the direct effect of privatization and liberalization on TFP growth. They show that market-oriented regulatory reforms significantly contributed to improving productivity in OECD countries during the Nineties, especially by reducing the gap from the technological frontier.[4] Pavcnik (2002) finds a direct impact of trade liberalization on productivity improvements, which works through the reallocation of resources to more efficient producers. Several other papers, instead, look at the effect of competition and entry on productivity growth (e.g., Griffith and Harrison, 2004, and Aghion et al., 2009). They use policy variables, such as the

[3]See also Sproul (1993), who finds that prices increase in industries after a cartel has been discovered and convicted; Clarke and Evenett (2003), who find that the vitamin cartel reduces cartel prices in jurisdictions where antitrust conviction is more likely and costly; and Voigt (2009), who finds a positive effect of a set of indicators of the quality of competition policy on total factor productivity, that however disappears when controlling for institutional quality.

[4]This results are partially critically challenged by Bourlès et al. (2010) and Amable et al. (2009).

introduction of the EU single market program or the UK privatization program, as instruments for competition, which is proxied by the price-cost margin, and entry. They show that these policies have a positive impact on competition and entry and these, in turn, increase productivity. Unlike these latter studies, we do not attempt to measure the channel through which competition policy affects productivity. First, this is not essential to our exercise as we want to assess the policy effectiveness. Second, in this way we avoid specifying any notion of competition which might be problematic both theoretically and empirically.[5]

The remainder of the paper is organized as follows. Section 2 presents and discusses our empirical model and the identification strategy. Section 3 presents the CPIs and the data sample. Section 4 discusses our results and performs some robustness checks. Section 5 briefly concludes. Further information about the variables' construction, as well as several additional regressions and robustness checks are reported in the on-line appendix.

2 Econometric Specification

The objective of competition policy is to deter behaviors that reduce competition. Therefore, the causal link between competition policy and efficiency goes through the impact of the former on market competition. Aghion and Schankerman (2004) provide a theoretical framework for explaining this link. They point out that competition-enhancing policies may improve productivity by facilitating the weeding out of less efficient firms;[6] by promoting cost reduction investments by incumbent firms;[7] and by encouraging entry of new, more efficient firms. Hence, to make robust causal inference on the effectiveness of competition policy, we analyze the direct link between the policy and TFP growth ($\Delta TFP_{i,j,t}$):[8]

[5]For instance, from a theoretical point of view, the price cost margin (PCM) is a poor indicator as it (imperfectly) captures only a short-run notion of competition. Even in this case, the relationship can be non linear and an increase in competition may result in a higher PCM (Boone, 2000).

[6]More generally, competition acts as a selection process that reallocates market shares in favor of the most productive firms. Haskel (2000) provides empirical evidence of this process. Disney et al. (2003) and Syverson (2004) show that competition reduces productivity dispersion suggesting that inefficient firms are forced to either catch-up or to exit.

[7]Competition also presses managers to reduce x-inefficiency (Hicks, 1935, Leibstein, 1966). This point is made theoretically by Nalebuff and Stiglitz (1983), while Vickers (1995), Nickell et al. (1997), Griffith (2001) and Bloom and Van Reenen (2007) provide empirical evidence of a positive relationship between competition and x-efficiency.

[8]While under strict neoclassical assumptions, TFP disembodies technical change or dynamic efficiency, in practice it integrates a range of other efficiency effects including those from organizational and institutional change,

$$\Delta TFP_{i,j,t} = \alpha + \beta CPI_{i,t-1} + \varepsilon_{i,j,t}, \quad (1)$$

where $CPI_{i,t}$ is one of our indicators of competition policy in country i at time t. Following the existing literature (e.g., Nicoletti and Scarpetta, 2003 and Griffith et al., 2004) we model the unobserved heterogeneity by means of an error term, which takes the form $\varepsilon_{i,j,t} = \psi_{i,j} + \phi_t + u_{i,j,t}$. The country-industry-specific fixed-effects $\psi_{i,j}$ account for the time-invariant unobserved heterogeneity and the full set of time dummies (ϕ_t) controls for common macroeconomic shocks that may affect TFP growth in all countries at the same time.[9]

Clearly, the rates of TFP growth are affected by other country-industry characteristics. Our preferred empirical specification builds on a general endogenous growth model (e.g., Aghion and Howitt, 2006). The basic idea is that laggard industries can catch up with the technological frontier by innovating or adopting the leading technologies. Therefore, the technological and organizational transfer from technology-frontier firms influences the productivity of laggard industries and, hence, their productivity is co-integrated with that of the leader. Under the assumption of long-run homogeneity, this process has an Error Correction Model (ECM) representation where the industry-level TFP growth ($\Delta TFP_{i,j,t}$) in country i and time t depends on the technology transfer from the country on the technological frontier ($TFP_{L,j,t}$), and the productivity gap or distance to the technological frontier ($TFP_{L,j,t}/TFP_{i,j,t}$) (e.g., Griffith et al., 2004, pg. 886). Moreover, following Griffith et al. (2004), we also assume that other observable industry-country-specific factors related to innovation – such as R&D intensity ($R\&D$) and human capital – directly affect the rate of TFP growth.[10] The equation that we estimate is, thus, the following:

$$\Delta TFP_{i,j,t} = \alpha + \beta CPI_{i,t-1} + \delta \Delta TFP_{L,j,t} - \sigma \frac{TFP_{L,j,t}}{TFP_{i,j,t}} + \gamma X_{i,j,t-1} + \chi Z_{i,t-1} + \psi_{i,j} + \phi_t + u_{i,j,t}, \quad (2)$$

changes in returns to scale, and unmeasured inputs such as research and development and other intangible investments (e.g., Inklaar et al., 2008). Moreover, industry-level TFP also captures the effects of the reallocation of market shares across firms.

[9] We run a large amount of alternative specifications to analyze how these assumptions on the error terms affect our results. This discussion is reported in more details in the on-line appendix. Neither the choice of different individual effects, nor the accounting of potential serial correlation in the residuals affect our main results.

[10] Differently from them, however, we do not analyze how R&D might indirectly affect TFP growth by shaping the catch-up process.

where $X_{i,j,t-1}$ are country-industry-specific control variables (human capital, trade openness, R&D, and a country-industry-specific trend), $Z_{i,t}$ are country-specific controls (product market regulation and the quality of institutions).

2.1 The Non-Linear Effects of Competition Policy

Inverted U-shape or not?

Potentially, competition policy might have a non-linear effect on productivity growth akin to the non-linear effect of competition on innovation identified in recent endogenous growth models.[11] In particular, Aghion et al. (2001) study a model of step-by-step innovation where both leaders and laggards produce and innovate. Laggards must first reach the leader's technological level before being able to challenge its leadership and replace it. Aghion et al. (2001) find that in most cases an increase in competition spurs innovation, as the standard negative Schumpeterian effect linked to lower rents is dominated by a positive 'escape-competition-effect'. Aghion et al. (2005), however, further develop this approach taking into account the probability that an industry is in a neck-and-neck situation. They predict an inverted U-shape for the relationship between competition and innovation, and find that this prediction is confirmed by firm-level data.

Hence, in principle we cannot rule out that competition policy, if too strict, may also have some adverse effects on efficiency. However, we think that the ambiguity of the impact of competition on innovation should not extend to competition policy. First, competition policy is less likely to have a strong impact in those markets where competition is already intense. Indeed, in most areas of competition law (i.e., vertical agreements, abuses of dominance and mergers) the pertinent prohibition applies only if the relevant market *significantly* departs from perfect competition (e.g., high concentration, high barriers to entry, large switching costs, etc.).[12] As for cartels, even if the prohibition applies irrespective of the competitive conditions of the market, they generally represent the most serious restriction of competition. Moreover, the idea

[11] See also Whinston and Segal (2007) and Acemoglu and Cao (2010) for alternative models pointing at contrasting effects of competition on innovation.

[12] In many of these areas antitrust law defines 'safe harbors' in terms of market shares or concentration indexes which establish a presumption of legality. For instance, in the European Union the legal and absolute presumptions are that some vertical restraints are compatible with competition law if none of the parties of the agreement has more than 30% of the relevant market.

that cartels foster innovation has been generally dismissed (Nocke, 2007). Second, in most jurisdictions, all the relevant antitrust prohibitions (again with the exception of cartels) admit an 'efficiency defense'. This defense is meant to allow conducts that, although reducing competition, improve efficiency and benefit consumers. Therefore, the 'efficiency defense' provides a protection for the investments firms make to innovate.[13] Our CPIs reflect the extent to which the various competition policy regimes allow this defense and, therefore, incorporate the protection of investments in the interpretation of the antitrust rules. Hence, our measure of competition policy takes a higher value (ceteris paribus) where the protection of investments is a goal that shapes the interpretation of the applicable rules. Combining these two considerations, we should expect a positive relationship between *good* competition policy and innovation.

To empirically validate this claim, we estimate two alternative specifications which are reported in the on-line appendix. First, we use a quadratic, rather than a linear, term for the Aggregate CPI. Second, we use a step function for low, medium, and high levels of the Aggregate CPI. In both cases we do not find evidence of such a non-linear effect, which makes us confident of the chosen linear specification (2).

The Interaction with the Technology Frontier

Some recent papers have suggested that competition-enhancing policies may also influence TFP growth through an indirect channel, by interacting with the distance to the technological frontier.[14] Indeed, competition policy, by increasing competition and reducing entry barriers, may increase the opportunities and incentives for the adoption of leading technologies. However, the returns from increasing productivity and improving efficiency in order to escape competitive pressure might be higher for firms competing neck-and-neck with rivals that are close to the technological frontier. Hence, the effect of competition policy might differ, depending on the level of technological development of a country-industry.[15] Therefore, we look at

[13]Baker (2007) argues that the application of modern economic theory has helped antitrust agencies to identify the types of firm's conduct and industry settings where antitrust interventions are most likely to foster innovation. Similarly, Gilbert (2008) maintains that antitrust policy has recognized the importance of finding a right balance between providing incentives to innovate and limiting practices that may harm competition.

[14]Similarly, some empirical studies recently analyzed the differential effect of product market regulation on productivity and innovation depending on the distance to the frontier (Nicoletti and Scarpetta, 2003, Amable et al., 2009, Bourlès et al., 2010).

[15]Indeed, Acemoglu et al. (2006) show that the selection of more efficient firms induced by competition is beneficial for countries close to the technological frontier where its effect on cutting-edge innovation is more important.

an additional specification where the effect of competition policy on TFP is interacted with the technology gap.

2.2 Identification

The identification of a causal link between competition policy and productivity growth crucially relies on the ability to account for the potential endogeneity of our key policy variables. Especially when looking at country-level aggregates, endogeneity might arise from omitted variable bias, as well as from two-way causality and measurement errors. In this paper we adopt a multi-steps approach, using several alternative strategies to pursue the ultimate goal of establishing a robust causal relationship between competition policy and TFP growth.

First, we believe that two-way causality is not a major concern in our case. In principle, the application of competition policy might be focused on less competitive and productive markets, which in turn might lead to a negative correlation between the CPIs and the error term. However, our CPIs aggregate several institutional characteristics, which are unlikely to respond swiftly to changes in TFP growth rates. Institutions slowly evolve over time quite independently of specific and short-run changes in market outcomes.[16] Even those variables that represent some relevant enforcement features, such as human and financial resources, depend on political decisions that generally take time to be put into practice. In any case, in order to reduce the potential bias resulting from two-way causality, we use lagged values of the policy variables with respect to our dependent variable. This is a standard approach that relies on the assumption that the lagged values of the policy are uncorrelated with the error terms of the estimated equation (e.g., Griffith et al., 2004 use this exclusion restriction to identify the causal effect of R&D on industry TFP growth).

The main identification issue in the context of our model is related to the existence of an omitted variable bias. The panel structure of our data-set allows us to control for time-invariant

Yet, selection may be harmful for countries far away from the frontier. Similarly, Aghion et al. (2009) find that the threat of technologically advanced entry increases incumbents' innovation in sectors close to the technology frontier, where an innovating incumbent can survive the entry of technologically advanced firms. Yet, it reduces innovation in laggard sectors where the threat of technologically advanced entry decreases the incumbent's expected rent from innovating.

[16] For instance, the introduction of leniency programs, or the adoption of the EU competition law model in Eastern European countries, are more likely to be the consequence of the diffusion of some institutional innovations, rather than a response to inadequate short-run market performances.

unobserved individual heterogeneity at the industry-country level through fixed-effects, as well as for time fixed-effects. However, there still might be time-varying unobserved heterogeneity. In particular, this might derive from the existence of several other competition-enhancing policies or, in general, other policies correlated with competition policy that might affect TFP growth rates. In our basic specifications, we control for those we believe to be the most prominent policies affecting competition (product market regulation, liberalization, and privatization) and for trade openness. We are confident that these controls should help mitigate the endogeneity problem. Nonetheless, we propose a twofold approach to provide further evidence on the causal nature of the link between competition policy and productivity growth.

First, we propose an instrumental variable approach, which allows us to explicitly test whether endogeneity matters and to control for another source of potential inconsistency of the OLS estimates: the existence of measurement errors. Following some recent contributions, which find political variables to determine policy outcomes (e.g., Besley and Case, 2000; Duso and Röller, 2003; Duso and Seldeslachts, 2010), we use the government's ideological position on regulatory issues as possible instruments.[17]

Second, in addition to the IV estimation, we adopt a less formal approach to improve our identification strategy, which looks at potential non-linear effects of competition policy on TFP growth. We search for situations where we expect competition policy to have a differential effect on productivity as compared to other omitted factors or policies. If we were to observe this kind of behavior in the data, this would enhance our confidence that the estimated nexus between the quality of a competition policy regime and TFP growth can be interpreted in a causal way. Although one can never fully rule out the possibility that some complex interactions of omitted shocks could drive the results, this would then seem unlikely. There are two dimensions of heterogeneity that we think are important in this respect. The first is related to country-specific characteristics. As discussed in section 2, we expect competition policy to be more ef-

[17] These variables are re-elaborated from the data by Woldendorp et al. programmatic position(2000), Cusack and Fuchs (2002), and Klingemann et al. (2006). They represent the weighted average programmatic position on particular economic issues of the government's parties. As weights, we used the number of each party's votes. As a robustness check, we also use an alternative set of instruments derived from a well-established practice in industrial organization (e.g., Hausman, 1997). This consists of using different aggregations of the potentially endogenous variables in other markets as an instrument for the same variables in the market of interest. This results are discussed in depth in the on-line appendix

fective in those countries where the quality of the legal institutions is higher. In fact, national courts are strongly involved in the enforcement of competition policy, as they often retain the power to adjudicate antitrust cases either directly or in appeal. Yet, crucially for our argument, courts are not involved in the adoption of other productivity-enhancing policies (for instance, regulation, R&D subsidies or fiscal policy) or, at least, they are involved only indirectly. The second dimension of heterogeneity we look at is related to industry-specific characteristics. Our data encompass industries belonging both to the manufacturing and service sectors. We expect the former to be significantly more affected by competition policy. The reason is that services are in general subject to strong sector-specific product market regulations – such as price control, entry regulations, and state ownership – which, in these industries, play a more significant role than competition policy in shaping the competitive environment and, hence, productivity outcomes. This intuition is empirically supported by Nicoletti and Scarpetta (2003) who find that deregulation plays a significantly greater role in fostering productivity in services than in manufacturing sectors. This kind of regulation clashes with competition policy, and for this reason we expect that competition policy will be less effective in those industries where the tightness of product market regulation is greater.[18]

3 Data Sample and Descriptive Statistics

We estimate our model (2) on a sample of 22 industries in 12 countries over the period 1995-2005. The countries included in the study are: Canada, the Czech Republic, France, Germany, Hungary, Italy, Japan, the Netherlands, Spain, Sweden, the UK, and the US.[19] We use data both at the national level and at the industry level. National level data are used to measure the policy variables (competition policy, product market regulation) and the quality of the institutions. The remaining variables are measured at the industry level, which belong both to the

[18] Clearly, other forms of regulation – e.g., health and safety regulations – might have an additional effect on productivity growth also in manufacturing industries. However, these regulations are inherently different from those policies that directly control the competitive process and, hence, should not affect our identification argument.

[19] These countries have been selected to be representative of different legal systems (common law and civil law), to include both EU and non-EU countries and, among the EU countries, both founding members and countries that have recently entered the Union, namely Hungary and the Czech Republic.

manufacturing and to the service sectors.[20]

In the following sections we briefly describe our main explanatory variables, the competition policy indexes, as well our dependent variables: TFP growth and labor productivity (LP) growth. These variables are discussed in depth in the on-line appendix, where we also describe the other independent variables, as well as the instruments used in our regression. Table 1 reports the preliminary statistics and a very short description for all variables.

3.1 Measuring the Quality of Competition Policy: The CPIs

The ultimate aim of competition policy is to maximize social welfare. Hence, the quality of a competition policy regime should be evaluated on the basis of the ability of this policy to deter firms that operate within its jurisdiction from undertaking those behaviors that, by impairing competition, reduce social welfare. In this section, we provide a self-contained discussion on how we measure the quality of a competition policy regime. We briefly discuss the theoretical background behind our data collection exercise, the measurement issues we faced, as well as the steps of the aggregation process we undertook to generate a set of summary indicators of the quality of competition policy, the CPIs. A more exhaustive discussion of all the issues touched upon in this section can be found in the companion paper (Buccirossi et al., 2011). Moreover, the on-line appendix provides a more in-depth overview of the properties of some of our indicators and their distributions.

Following Becker's (1968) theory of optimal deterrence, we consider that the level of deterrence of competition policy is determined by three fundamental elements: the size of the sanctions, the probability of detection and conviction, and the probability of errors. Several institutional and enforcement features of a competition policy regime might affect these three factors (see Buccirossi et al., 2009). The features which we believe have the strongest impact on the level of deterrence of anti-competitive behaviors are: the degree of independence of the competition authority with respect to political or economic interests (formal independence);

[20]The 22 industries (ISIC rev.3 codes) included in the study are the following: agriculture, forestry and fishing; mining and quarrying; food products; textile, clothing and leather; wood products; paper, printing and publishing; petroleum and coal products; chemical products; rubber and plastics; non-metallic mineral products; metal products; machinery; electrical and optical equipment; transport equipment; furniture and miscellaneous manufacturing; electricity, gas and water; constructions; hotels and restaurants; transport & storage; communication; financial intermediation; business services.

the separation between the adjudicator and the prosecutor in a competition case (separation of powers); how close the rules that make the partition between legal and illegal conducts are to their effect on social welfare (the quality of the law on the books); the scope of the investigative powers the competition authority holds (powers during investigation); the level of the overall loss that can be imposed on firms and their employees if these are convicted (sanctions and damages); the toughness of a competition authority, which is given by its level of activity and the size of the sanctions that are imposed on firms and their employees in the event of a conviction, and the amount and the quality of the financial and human resources a competition authority can rely on when performing its tasks.

We collected information on each of these features, by asking several specific questions.[21] We gathered these data separately for the three possible infringements of the antitrust legislation (hard-core cartels, other anti-competitive agreements, and abuses of dominance) and for the merger control policy in each country and for each of the years in the sample. Most of this information was directly obtained from the competition authorities of the 13 jurisdictions included in our sample through a tailored questionnaire.[22] The data obtained from this survey were integrated with information derived from the country studies carried out by the OECD in the context of its reviews of regulatory reforms, from the chapters on competition and economic performance in the OECD Economic Surveys and from the competition authorities' own websites and publications.[23] Despite this extensive data gathering exercise, we encoun-

[21]For instance, to measure the quality of the law, we collected information on the standard of proof that is required when deciding on a specific type of violation, as well as the nature of the goals that inform the decision-making process. To measure the competition authority's powers during investigations we collected information on the power to impose, or request, interim measures; the powers to gather information by inspecting the premises of the firms under investigation or the private premises of the firms' employees; the powers to gather information by wiretapping the conversations of the firms' employees. Buccirossi et al (2011) describes all these issues in depth.

[22]Our sample includes 12 countries and 13 jurisdictions, as it includes the European Union. We only surveyed the competition authorities which are either independent public bodies or ministerial agencies/departments, while we did not survey the courts (but we have collected data on their powers and activities). The bodies surveyed are: Competition Bureau (Canada); Urad pro ochranu hospodarske souteze (Czech Republic); Directorate General for Competition Affairs (European Union); Conseil de la Concurrence (France); Direction Gènèrale de la Concurrence (France); Bundeskartellaamt (Germany); Gazdasági Versenyhivatal (Hungary); Autorità Garante della Concorrenza e del Mercato (Italy); Japan Fair Trade Commission (Japan); Nederlandse Mededingingsautoriteit (the Netherlands); Servicio de Defensa de la Competencia (Spain); Tribunal de Defensa de la Competencia (Spain); Konkurrensverket (Sweden); Office of Fair trading (UK); Competition Commission (UK); Federal Trade Commission (US); Antitrust Division - Department of Justice (US).

[23]Despite the active collaboration of most competition authorities, it was not possible to collect all data on the enforcement characteristics of the competition policy necessary to build the CPIs for the period considered. Hence, our database has a few missing observations. We tried to fill the gaps by asking the competition authorities to

tered some difficulties in obtaining data on the toughness of the competition authorities and we could include in our database only details on the maximum jail term imposed on managers of firms involved in hard-core cartels (for those jurisdiction that have this type of sanction) and the number of hard-core cartels and mergers investigated every year.[24]

The CPIs have a pyramidal structure.[25] We collected data for each of the seven key features of competition policy mentioned above. Each piece of information was then assigned a score, on a scale of 0-1, against a benchmark of generally agreed best practice (from worst to best).[26] The best practice is determined by relying on scientific papers and books, on documents prepared by international organizations such as the International Competition Network and the OECD, and on our judgement. All the information on a specific policy feature was summarized in a separate low-level index using a set of weights to linearly aggregate it.[27] We calculated separate indexes for each of the three possible competition law infringements and for mergers, to take into account the differences in the legal framework and, where possible, in the enforcement.[28]

provide us with an imputation of the missing observations based either on other data at their disposal or on their historical knowledge of the trends. When this was not possible, we performed some limited imputation of the missing data, whenever this was allowed by the characteristics of the other available data on that specific feature. Nevertheless, the database still has some gaps. This means that in some cases we do not have all the information necessary to calculate a specific index. To avoid calculating indexes whose value could be altered by the lack of information, we do not calculate an index (at any level of aggregation) if 50%, or more, of the relevant information content was missing, which however happened in very few cases.

[24]Therefore, it is clear that our measure of enforcement is less accurate than our measure of institutions. However, our CPIs capture most of the features that have a likely impact on the deterrence properties of the analyzed competition policy regimes as they fully describe their institutional features and proxy the level of enforcement by important variables such as the budget dedicated to the implementation of this policy, the amount of human resources devoted to the same aim and their quality. Furthermore, we believe that the institutional features of a competition policy regime play the greatest role in determining its effectiveness. As Kovacic (2009, 145) recently pointed out: "Good policy runs on an infrastructure of institutions, and broadband-quality policy cannot be delivered on dial-up-quality institutions." Hence, one can see good institutions as a necessary, yet possibly not sufficient, condition for a good enforcement.

[25]Our methodology is akin to the one developed by the OECD for the indicators of product market regulations (PMR) and the competition law and policy indexes (CPL). See Boylaud, Nicoletti, and Scarpetta (2000), Conway and Nicoletti (2005) Conway and Nicoletti (2006) for the former and Høj (2007) for the latter.

[26]When a data entry is quantitative it is normalized by dividing it by the highest corresponding value held by any competition authority in the sample, so that even quantitative information assumes a value between 0-1.

[27]We are aware that there might be complementarities among different aspects of competition policy that we may miss by using this linearly additive specification. However, we believe that it would be difficult to choose a more precise approximation of the relationship that could exist between these variables. Hence, we have selected this aggregation form that has the advantage of being simple and at the same time rather complete.

[28]This was not always easy. For example, the competition authorities rarely have separate divisions that deal with the different types of infringements, hence we could not obtain separate data on the resources employed for each of them. Hence, the resource index takes the same value for all the three possible antitrust infringements, as well as for merger control.

The low-level indicators were subsequently aggregated into two medium-level indexes for each of three types of possible competition law infringements and for mergers: one which summarizes the institutional features of the competition policy regime and one which summarizes its enforcement features. The medium-level indexes were then aggregated to form a number of different summary indexes. More specifically, we calculated (for each country and each year in the sample): i) one index that measures the deterrence properties of the competition policy regime with regard to all antitrust infringements (the Antitrust CPI) and one that measures its deterrence properties in the merger control process (the Mergers CPI); ii) one index that assesses the institutional features (the Institutional CPI) and one that assesses the enforcement features (the Enforcement CPI); iii) a single index that incorporates all the information on the competition policy regime in a jurisdiction (the Aggregate CPI).

The weights employed in this aggregation process are based on the relevance that each item, in our view, deserves.[29] However, to check whether our choice of weights has a decisive influence on the results, we also used three alternative weighting schemes. The first uses an agnostic approach and weights each piece of information equally. The second, aggregates the features of competition policy using factor analysis.[30] The correlation coefficients between the values of the Aggregate CPIs built with our weights and these two alternative CPIs, one built with equal weights and one based on the weights obtained from the factor analysis, take very high values (0.97 and 0.96 respectively) and they are significantly different from zero at the 1% level. In the robustness section we run our basic regression using the CPIs calculated by means of these alternative weighting schemes and show that the results are robust. The third alternative weighting scheme is based on random weights. We randomly generate, from a uniform distribution (0,1), 1,000 sets of weights, which are then normalized to sum to one. For each of these sets, we build one Aggregate CPI. In the results section, we report the distribution of the coefficients estimates for these 1,000 Aggregate CPIs and we show that our main findings are not affected.

[29]We have been very conservative in the choice of the weights and we departed from equal weights only for situations for which there were robust theoretical reasons to do so. Moreover, we tried to be as transparent and explicit as possible in explaining why we chose each particular weight. The in-depth description of these issues can be found in Buccirossi et al. (2011).

[30]A complete description of this alternative methodology and the results can be found in Buccirossi et al. (2011).

3.2 Dependent Variables

In this section we shortly describe our main dependent variables: TFP and LP growth. An in-depth description of the productivity-related measures is provided in the on-line appendix.

The measure of TFP growth comes from the EU-KLEMS database.[31] TFP growth is measured by the Solow residual within the growth accounting framework under certain restrictive assumptions. One of these assumptions is that prices are equal to marginal costs. Following Griffith et al. (2006), we relax this assumption by multiplying the labor and capital shares by the industry-level mark-up, which is estimated as the ratio between industry-level value added and labor and capital costs (see Paquet and Roubidoux, 2001).[32] In our sample, the average TFP growth at the industry level ranges between -1.7% for the business services sector and 3.7% for the communications sector. The average TFP growth in the entire sample is 0.0096%.

We then use TFP levels to determine the technology frontier at the country-industry level and the technology gap between each country-industry and the frontier. Following the existing literature (Griffith et al., 2004; Nicoletti and Scarpetta, 2003), we obtain the technology gap using a two-step procedure. First, we calculate the ratio between the level of TFP in each country-industry and the geometric mean of the TFP levels in all the countries included in the sample for that industry. The frontier is defined as the country-industry with the highest ratio. Second, we obtain the technology gap by subtracting all the observed country-industry ratios from the frontier ratio.

While TFP growth is a rich measure, which incorporates the effects of all inputs on production, it might be argued that it might be affected by measurement errors due to its complexity. Therefore, we also use an alterative and much simpler measure of efficiency represented by labor productivity (LP) growth as measured by value added per worker. When we use LP

[31] The EU-KLEMS project is funded by the European Commission, Research Directorate General as part of the 6th Framework Programme, Priority 8, 'Policy Support and Anticipating Scientific and Technological Needs'. The aim of the project is to create a database on measures of economic growth, productivity, employment creation, capital formation and technological change at the industry level for all European Union member states plus selected non-European countries from 1970 onwards. For a short overview of the methodology and results of the EU KLEMS database, see Timmer et al. (2007).

[32] The concerns that we expressed on the ability of the mark-up to measure the intensity of competition in a market are not necessarily relevant for the correction implemented in the calculation of the Solow residual. Indeed, this correction cleans the TFP measure of the error due to the existence of a divergence between price and marginal cost (the mark-up).

growth as a dependent variable in our regressions, we re-define the frontier variables (the LP of the leader and the technology gap) accordingly.

3.3 Simple Correlations

Before moving to our estimation results and to motivate our regression analysis, we look at simple correlations. We start by looking at the correlation between TFP growth and the CPI at the country-aggregate level. We compute a weighted average for TFP growth using the industry value added as a weight. The correlation coefficient is large and positive (0.29) and significantly different from zero at the 1% level. We calculate a positive correlation between the average TFP growth and the CPI for most of the countries. In particular, we calculate a positive and significant correlation coefficient for the Czech Republic (0.83), France (0.32), Germany (0.43), Hungary (0.13), Japan (0.21), the Netherlands (0.39), and the UK (0.51).

Furthermore, there is a substantial variation in TFP growth measures among the 22 industries within a country. In this study we also exploit this heterogeneity dimension, as competition policy might affect various industries in a different way. We make use of this argument as an additional step in our identification strategy. Accordingly, we also look at the pairwise correlation between the CPI and TFP growth at the industry-country level. Again, this correlation is positive (0.08) and significantly different from zero at the 1% level. Our empirical model starts from this simple correlation to identify the causal effect of the policy.

4 The Results

We first consider the simple, average effect of competition policy on TFP growth and LP growth by using the various CPI indexes discussed in section 3.1 and estimating equations (1) and (2). In all regressions we include year dummies and industry-country fixed-effects to control for unobserved heterogeneity among industries and countries, as well as for time fixed effects. When estimating model (2), we further control for other competition-enhancing policies as measured by the OECD PMR index, trade liberalization, a country-industry-specific deviation from the trend to account for potentially different business cycles at the country-industry level. Finally, we also control for the frontier-related measures which we previously discussed in section 2.

Most of the explanatory variables are lagged by one year to reduce possible endogeneity issues. Standard errors are clustered at the country level to allow for correlation among industries in the same country. We estimate the model by OLS. After discarding some extreme outliers, our sample consists of 1,847 country-industry-time observations.[33]

4.1 The Basic Model

In column 1 of table 2 we report the results of the basic specification of model (1). The key result is that the coefficient estimate for the Aggregate CPI is positive (0.0924) and statistically significant at the 1% level: good competition policy is positively correlated to productivity growth in a statistically significant way. Our main result persists if we use an equal-weighted Aggregate CPI (column 2) instead of using our preferred weighting scheme, as well as if we use labor productivity growth as an alternative dependent variable (column 3).

We then move to our preferred and richer specification described in model (2), where we control for the TFP level at the technological frontier, the technology gap, and other competition-enhancing policies. Again, we estimate a positive and significant impact of competition policy on productivity growth, independently of whether we use our preferred Aggregated CPI measure (column 4), the equal-weighted Aggregated CPI (column 5), or if we use labor productivity (column 6) as the dependent variable. These estimates also indicate significant effect from an economic point of view. For instance, a coefficient estimate of 0.09 for the aggregate CPI implies an average elasticity of TFP growth with respect to the aggregate CPI of around 4.48 at the mean value of the variables.[34] Estimates for all the other control variables conform to our expectations and to previous results reported in the literature. This gives us confidence about the quality of our preferred specification. In particular, we find that the TFP level of the leader, the technology gap, and import penetration have a positive and significant impact on TFP/LP growth; while product market regulation, in the form of barriers to competition, has a

[33]We dropped the observations corresponding to the first and the last percentiles of the TFP growth distribution.

[34] To give a more concrete idea of the economic meaning of this estimate, we can look at one example such as the 'food products' industry in the UK. In this industry, TFP growth in 2001 was 3.2%, while in 2002 it was 5.2%, with an increase of 62.5%. In the same year, the UK Aggregate CPI increased by 4.6%. According to the estimated elasticity, the improvement of competition policy in the UK, as represented by the increase in the CPI, is responsible for 22.1% of the actual increase of TFP growth. Hence, without the improvement of the UK competition policy, TFP growth in 2002 would have been of 4.53% (3.2% * (1 +(0.619-0.221)).

negative effect on productivity growth, though this is not significant,policy runs on mimicking the findings by Nicoletti and Scarpetta (2003). Finally, the country-industry-specific trend that we inserted to account for short-run cyclical fluctuations in demand also has a positive and significant impact.[35]

The last column (7) reports the results from the specification where we assume that competition policy might affect TFP growth differently depending on the country-industry's distance from the frontier. In this specification, we define three categories for the technology gap (low, medium, high) and allow the coefficient for the CPI to differ among them.[36] The estimated effect of competition policy is much larger and more significant (0.124) for country-industries far away from the frontier than for country-industries close to the frontier (0.053). This result is in line with the empirical findings of Nicoletti and Scarpetta (2003), who show that liberalization is mostly beneficial for productivity in manufacturing industries the further a given country is from the technology leader. Hence, increasing competition through an effective competition policy (or reducing entry-limiting regulations) may facilitate the adoption and development of advanced technologies, which in turn increases productivity. The benefits of increasing competition in country-industries close to the technological frontier seem, instead, to be more modest, yet still positive and significant.[37]

We then move to analyze the impact of the various dimensions of competition policy as measured by our disaggregated indexes. In table 3, we focus on the difference between institutions and enforcement in columns 1 and 2 and between mergers and antitrust in columns 3 and

[35]As we mentioned in section 2, there are two other important control variables – R&D and human capital – for which we unfortunately have many missing values. We run several additional regressions controlling for these two major drivers of productivity growth and our results are not affected. We report and discuss these specifications in the on-line appendix.

[36]We define the three dummies according to the distribution of the gap variable: low level (up to the 33rd percentile of the distribution), medium level (from the 33rd to the 66th percentile), and high level (from the 66th percentile).

[37]These empirical findings might, at first glance, appear at odds with the theoretical framework proposed by Acemoglu et al. (2006), who show that a limited level of competition might be beneficial for sectors far away from the frontier, as we discussed in section 2. These are 'adopter' sectors that find it optimal to pursue an investment-based strategy rather than selecting high-skill managers and firms through a highly competitive process, which is necessary for innovation. Yet, our results do not necessarily refute this theoretical argument, as they might rather be driven by the fact that the country-industries in our sample are not, on average, so far from the technological frontier to switch to the investment-based strategy. This seems plausible in our context, as all countries in our sample are quite homogenous, as they are all members of the OECD. Indeed, the empirical evidence put forward by Acemoglu et al. (2006) is based on data for non-OECD countries so as to approximate real technology 'followers' which are significantly behind the world frontier.

4. Again, we obtain results similar to those observed in our basic specifications: the various dimensions of competition policy have a positive and significant effect on productivity growth. With the exception of the Antitrust CPI, the size of the effect is, however, always smaller than the one measured by the Aggregate CPI and, in some cases, it is also less significant. In particular, the results for the Enforcement CPI are the weakest, as the coefficient estimate drops to 0.04 and loses significance. Our interpretation for this result lies in the quality of the information summarized in this index. As previously mentioned, the only complete and reliable measure of antitrust enforcement relies on the level and quality of their monetary and human resources.

The established positive and significant relationship between the quality of competition policy, and in particular of its institutional design in the area of antitrust, and productivity growth is the key finding of this study. As we discussed thoroughly in section 2.2, one major concern for the causal interpretation of this effect is the potential endogeneity of the policy. In this section we started to address this issue by lagging the policy variables and controlling for most of the determinants of productivity growth discussed in the literature. The next sections aim at providing further evidence to give more confidence in the causal nature of the established link between competition policy and productivity growth.

4.2 Instrumental Variables

The next step that we propose in terms of identification strategy is to use an instrumental variables (IV) approach. The results of these IV estimations are reported in table 4. Following Duso and Röller (2003) and Duso and Seldeslachts (2010), we use political variables related to the government's programmatic position toward competition and regulation as instruments for the policy. Independent of whether we instrument only for the Aggregate CPI (columns 1, 3, and 5), or for both the Aggregate CPI and PMR (columns 2, 4, and 6), whether we use our preferred Aggregate CPI (columns 1 and 2) or the CPI based on equal weighting (columns 3 and4), we always find a positive and (almost always) significant coefficient estimate for the Aggregate CPI. This is even larger in size than that reported in our basic OLS specifications.[38] This result

[38]In the specifications where we use LP as a measure of productivity, the CPI's impact is positive but not significant at the usual confidence levels. This is due to an increase in the estimated robust standard errors. The p-values of the estimated coefficients are equal to 0.2 so that we cannot reject the null hypothesis that the coefficients estimates are positive at the 10% level.

is reassuring, as IV estimates are consistent in the presence of endogeneity. The instruments used seem to work properly: they are correlated to the instrumented variables, as shown by the high values taken by the F-statistic for the excluded instruments, as well as the high value of the partial R-squared of the excluded instruments in the first-stage regressions. High values of the robust Kleibergen-Paap Wald rk F statistic signal that the instruments are not 'weak' in the sense of Staiger and Stock (1997). Furthermore, the instruments are not correlated with the error term as shown by the Hansen J statistic.[39] Although always consistent, IV estimates are not efficient in the absence of endogeneity. Hence, we run a Wu-Hausman test of endogeneity and cannot reject the null hypothesis that the policies are exogenous at the 1% level.

These sets of results confirm our claim that the established positive link between competition policy and productivity growth can be interpreted in a causal way, as they allow us to reject the hypothesis that the policies are endogenous. Therefore, from now on we will focus on the OLS estimates which, in the absence of endogeneity, are more efficient.

4.3 Non-Linearities

In the final, informal, step of our identification strategy we exploit the possible non-linear effect of competition policy. The idea is that competition policy should be more effective in some countries than in others, due to their better institutional environment, and in those sectors which are less subject to industry-specific regulations. This should not be the case for other (omitted) policies. Moreover, the analysis of such non-linearities with respect to the institutional details is an important contribution on a more theoretical basis, as it allows us to identify the existence of complementarities between competition policy and the efficiency of (legal) institutions and, therefore, to provide a novel contribution to a recently expanding literature (Aghion et Howitt, 2006). These results are reported in table 6.[40]

In the first column, we present our basic specification where we simultaneously control

[39]In table 5, we report the first-stage regressions for the IV specifications of table 4. As expected, a pro-regulation attitude of the government (**per403**) and a pro-welfare limitation programmatic position (**per404**) are, respectively, negatively and positively correlated to the CPI (CPI_equal_weights) and positively and negatively correlated to PMR. A pro-EU attitude (**per104**) correlates positively with the CPI and negatively with the PMR index, which is consistent with the tendency of the European Commission to support the development of more competitive markets.

[40]Notice that, for lack of space, we do not report the coefficient estimates for all control variables as they are anyway very similar to those reported in our previous regressions.

for several institutional dimensions. Institutions seem to have a significant direct impact on productivity growth. Yet, unlike previous studies (e.g., Voigt, 2009), the positive and significant effect of competition policy is not affected by these additional controls. This reinforces the view that our indicators are able to capture the specific features of a competition policy regime, which we aimed to measure, and not the general quality of a country's institutional environment.

In column 2 we then interact the Aggregate CPI with the dummies for legal origins. While the effectiveness of competition policy is significantly higher in countries with German and Nordic legal origins, it is clearly less so in countries with French legal origins, which in our sample are France, Italy, and Spain. These results seem to be in line with findings reviewed by La Porta et al. (2008) who report that countries with civil law are associated with a heavier-hand regulation, which has an adverse impact on markets and economic performance.

We then explore which characteristics of a legal system are important drivers of competition policy effectiveness. To exploit in the best possible way the limited variation in our institutional data and, at the same time, to allow for non-linear effects through a step function, we have transformed our continuous institutional variables into categorical variables based on their distribution. Thus, for each institutional variable, we have defined three dummies: low level '*l*' (up to the 33rd percentile of the distribution), medium level '*m*' (from the 33rd to the 66th percentile), and high level '*h*' (from the 66th percentile) of institutional quality. Finally, we interact these dummies with the Aggregate CPI.

In column 3 we report results for the specification where we interact the Aggregate CPI with the dummies measuring the cost of enforcing contract (EC).[41] Although competition policy seems to have a positive and significant effect, independently of the levels of contract enforcement, the effect is substantially larger – indeed more than double (0.240) – for those countries with low enforcement costs (CPI_lEC). Hence, our results support the view that competition policy effectiveness might be stronger in countries where law enforcement is more efficient. In columns 4 and 5 we report the results of the specifications where we interact the Aggregate CPI

[41] Very similar results are obtained by using the general index for contract enforcement. However, in that case we lose Italy since there is no information on the time needed to enforce the contracts for this country.

with the Fraser 'Rule of Law' (RL) index and the WGI's 'Legal System' (LS) index.[42] In both cases, we observe competition policy to be less effective in countries with less efficient legal institutions, such as countries with a low rule of law or a poor legal system.

The reported results point to complementarities between competition policy and some dimensions of the legal institutions. This does not mean that policies in countries with a worse legal system or higher costs of enforcing contracts must be ineffective, but rather that their (partial) ineffectiveness can be better explained by the bad functioning of the more general legal institutions. Therefore, policy changes in these countries must be adequately designed to account for the additional constraints posed by the legal system.

The second dimension of heterogeneity of the degree of competition policy's effectiveness is industry-specific. As we pointed out, most of the service industries in our sample (e.g., electricity, gas, water, communication, financial intermediation) are subject to more or less heavy-handed sector-specific regulations and the organization of competition in these industries is delegated to sectoral authorities. Our claim is, therefore, that competition policy should have less of a bite in such industries, but this should not necessarily be true for other productivity-enhancing policies (e.g., fiscal policy and labor regulations). We report the results of the specification where we estimate separate coefficients for the Aggregate CPI, as well as for PMR in service and manufacturing sectors in column 6 of table 6. For the Aggregate CPI, we find a large (0.143) and statistically significant coefficient estimate in the manufacturing sectors, while the coefficient is much smaller and not significant in the service industries. Moreover, similarly to Nicoletti and Scarpetta (2003), we find that the coefficient of product market regulation is negative and significant in services but not in the manufacturing industries.[43] These results perfectly conform with our expectations.

All results reported in this section point to the existence of significant and sizable non-linear effects of competition policy on productivity growth. The estimated differential effects should not be expected for other public policies, which might constitute our problematic omitted fac-

[42]We also try specifications where we use sub-components of the legal system index, specifically 'Independence of the Judiciary' and 'Impartiality of the Courts' and find similar results.

[43]We also tried to disaggregate this result even more and estimate industry-specific coefficients for the Aggregate CPI and the PMR indicators. The Aggregate CPI has a significant impact exclusively in manufacturing industries while the PMR indicator mostly in service industries.

tors and generate endogeneity issues that would invalidate our causal inference. Hence, these further results might be seen as an additional step, which makes us more confident of the causal nature of the link we identify.

4.4 Extensions and Robustness Checks

Finally, we perform several robustness checks by using different CPIs and different measures for productivity growth, as well as different sample sizes.

First, to show that our results are not driven by the subjective weights we have chosen to build the CPIs, we use the two additional weighting schemes, which were discussed in brief in section 3.1. In column 1 of table 7, we report the results obtained when using the Aggregate CPI constructed using the weights generated by factor analysis. Our results are unchanged and competition policy still has a positive and significant impact on TFP growth at the 5% level, with a point estimates for the policy effect of 0.0726. As an additional robustness check, we run 1,000 regressions, each using a different Aggregate CPI generated with a different set of weights randomly drawn from a uniform distribution (0,1). Therefore, we obtain estimates for 1,000 β coefficients and their relative t-statistics, whose distributions are represented in figure 1. The distribution of the coefficients, which is represented in the first panel, ranges between 0.052 and 0.11, with a mean value of 0.084, which is close to our estimate in the basic specification. As shown by the second panel of the figure, all of the 1,000 coefficient estimates are statistically significantly different from zero (the lowest t-value is 2.98).

A second concern with the CPIs relates to the role of the EU competition policy in the EU member states. To correctly evaluate the effectiveness of each EU member state's competition policy, it is necessary to account for the fact the EU competition policy works alongside the national one. Therefore, for these countries, we have built a set of CPIs which are an average of each member states individual index and the EU index.[44] The coefficient estimate for the Aggregate CPI (column 2) is still positive, highly significant and larger in size (0.115) with respect to our basic specification. This means that EU competition policy improves, on average,

[44]Unfortunately, DG Competition did not provide us with information on enforcement features (such as the budget and the composition of the staff), at the EU level. Hence, we can only use information about EU institutional features. The precise definition of the variable is, thus, as follows: $AggregateCPI\_EU_{it} = \frac{2}{3}(0.5 * Institutions\_CPI_{it} + 0.5 * Institutions\_CPI_{EU,t}) + \frac{1}{3}Enforcement\_CPI_{it}$

the effectiveness of national competition policies.

Third, we need to consider the limitations of the TFP measure we use. Until now, following Griffith et al. (2004), we have used a measure for TFP growth corrected for the mark-ups (as measured by the PCM) to account for imperfect competition. However, one may have some concerns about the quality of an industry-level aggregated PCM measure. Hence, we propose an alternative specification where we use TFP measures (i.e., the growth rate, TFP of the leader, and the technology gap) which are not corrected for the mark-ups. The coefficient estimate reported in column 3 is still positive and significant at the 10% level.

Fourth, one might be concerned about the frequency of the data. TFP measures change quickly over time as a response to demand shocks, while our policy measures, although showing some significant time variation, present much more inertia. Therefore, we change the frequency of the data and look at the long-run effects. We propose three different specifications along this dimension. In the first one, whose results are reported in column 5, we take longer lags (three-year) for all explanatory variables. Still, the coefficient of interest is similar in size to that of our basic specification, though it loses a bit of significance, as expected given the long lag used. In the second robustness check (column 6), we define TFP growth over a time span of three years, and sum up the figures between year t and year $t+2$. We then 'lag' all explanatory variables by taking their value at the initial year, i.e., we look at how the value of competition policy in year t affects TFP growth between year t and t+2. In doing so, the number of observations is obviously reduced. We still find a positive and significant coefficient estimate (0.332) for the Aggregate CPI. As expected the coefficient is much larger, as it represents the effect of the policy on the three-year TFP growth rate. In the final specification, we use three-year averages for all variables (column 7). Also in this case, the coefficient estimate for the Aggregate CPIs is positive (0.0903) and significant.[45]

Fifth, one might be concerned that the right level of aggregation of our data should be the country rather than the industry, as the main interest of our study is in the impact of a national policy. In Section 3.3 we reported a significant simple positive correlation between country-

[45]Similar, though a bit less significant, results are obtained using a five-year interval. The loss of significance is due to the imprecision of the point estimation deriving from the reduction of the data variability via the aggregation process.

level TFP growth and competition policy. In this robustness check, we re-estimate our model by taking weighted averages of all our industry-specific variables using the value added of the industry as a weight (column 8). Also in this case, the coefficient estimate for the Aggregate CPIs is positive (0.0417) and significantly different from zero at the 10% level.

Finally, given the heterogeneity of competition policy's effectiveness across countries and industries, one might be concerned that our average results do not hold to the exclusions of particular countries and/or industries. Hence, we run our basic regression on several sub-samples, sequentially excluding one or two countries (156 sub-samples) or one or two industries (506 sub-samples). For each sub-sample, we run our basic regression. The distribution of the β coefficients and their t-statistics are represented in figures 2 and 3. In all sub-samples, our estimates for the CPI are positive and, in the very large majority of the cases (99.4%), they are statistically significant at least at the 10% confidence level. While none of the estimates are insignificant when we exclude one or two industries, only in 4 out of the 156 sub-samples where we simultaneously exclude two countries are the coefficients significantly positive (one-tailed test) yet not significantly different from zero (two-tailed test).[46]

4.5 Where does Identification come from?

We can show that there is significant and quite continuous within-country variation in the Aggregate CPI in almost all countries, which identifies our policy effect (see the on-line appendix for a graphical representation). Nevertheless, in this section we try to spot which specific policy changes in the Aggregate CPI might be the major identifier of the average increase in TFP growth estimated in our regressions.

In figure 4 we plot the evolution of the average *residual* TFP growth and its 95% confidence interval across the 22 industries of each country, as well as the competition policy indexes over the period 1995-2005. To mimic our estimation and control for sources of observable heterogeneity, we use the *residual* component of TFP growth which is not explained by the fixed-

[46]The only specification for which the t-value is further apart from a critical level (p-value of 0.21) is when we *simultaneously* exclude the UK and the Czech Republic. The reason is that the coefficient estimates drop to 0.04, while the standard error increases a bit with respect to our basic specification. Notice, however that, even in this unique case, we still cannot reject the null hypothesis of the coefficient being positive at the 10% significance level with a one-tailed test.

effects and the other variables included in our model (2) – excluding, of course, the Aggregate CPI. Again, we observe clear correlation patterns between the evolution of the Aggregate CPIs and of the residual average TFP growth. Our attention focuses on the evolution in the subset of countries and time periods for which the changes in policy are more noticeable and, therefore, are most likely to influence the average effect identified in our estimation.

The first country that appears to drive the estimated relationship is the Netherlands: the residual TFP growth rises between 2003 and 2004, and then decreases between 2004 and 2005. The same pattern with a lag is observed for the aggregate CPI, which rises in 2003 following an upward trend in the investment in human and financial resources and then goes slightly down, again because of a contraction in the resources allocated to the competition authorities. In the UK, over the 2000-2003 period, we also observe a strong correlation between the rise of residual TFP growth and the evolution of the aggregate CPI index. Such evolution is due to a steady growth in the financial and human resources available to the two competition authorities after the introduction of the Competition Act in 2000. In the USA, the period between 1999 and 2003 seems to be the one that identifies a positive link between residual TFP growth and the CPIs, as the two series follow a much correlated pattern. The residual productivity growth performance is accompanied by an increase in the budget/gdp ratio in the US competition authorities, as well as by an increase in the human resources.

In Hungary, we observe a common upward trend in residual productivity growth and competition policy. The major institutional changes that mark the evolution of the Hungarian competition policy are the attribution of more investigative powers to the competition authority and the modification of the criteria for setting the level of the sanctions. The latter are no longer based on the discretionary decisions of the competition authority, but are based on firms' turnover. These new tools were introduced starting from 2000. Moreover, a budget increase took place in 2002. A similar common upward trend can be observed in the Czech Republic. Indeed, while the residual productivity growth is constantly increasing, the competition policy experiences a slight increase due to the larger amount of resources available to the competition authority. On the institutional side, an important change happened around 1998 when the competition authority was attributed the power to investigate business premises.

5 Conclusions

The aim of competition policy is to ensure that firms undertake the least possible number of behaviors that reduce social welfare by impairing competition. Hence, an effective competition policy is one that deters most anti-competitive practices. Since by deterring anti-competitive practices competition policy should make markets work effectively and foster efficiency, in this paper we evaluate the direct impact of competition policy on efficiency. Hence, we estimate the effect of the key institutional and enforcement features of a competition policy, summarized in a set of indicators, the CPIs, on productivity growth in 22 industries of 12 OECD countries between 1995 and 2005.

Our results imply that good competition policy has a strong impact on TFP growth. The coefficient for the Aggregate CPIs is positive and statistically significant in a variety of specifications of our model. The Aggregate CPI also remains highly significant when we control for several other industry-country-specific factors, frontier-related variables, as well as the quality of a country's institutions. All these variables have a direct impact on TFP growth, but do not alter the fact that competition policy is effective in increasing productivity. We obtain similar results when we look at a more disaggregated picture and separately consider the effects of a competition policy's institutional and enforcement characteristics and when we differentiate between the policing of antitrust infringements and the merger control discipline. Yet, the institutional and the antitrust elements of the competition policy appear to have the strongest impact on TFP growth. We adopt a multi-steps approach to identification based on instrumental variable regressions and the exploitation of non-linearities. Therefore, we provide additional support to our claim that the established link between competition policy and TFP growth is of a causal nature. Furthermore, we observe complementarities between competition policy and the quality of legal institutions. The effect of the former is indeed larger in those countries where the enforcement costs are low and the legal system more efficient. Finally, our main findings prove to be robust to several checks, such as various measures of productivity, different aggregation techniques for the CPIs, and several sub-samples.

Our results provide support for the argument that competition policy creates gross benefits to the long-term performance of a country's economy. Nevertheless, these benefits should be compared with the costs of introducing competition laws and enforcing competition policy to perform a complete welfare assessment. Unfortunately, we did not have access to sufficiently precise and encompassing cost estimates to allow us to undertake such an analysis, which could, however, be undertaken in future work subject to further data collection. There is also scope for further refinements. Currently, we have used data on 22 industries in 12 OECD countries over ten years, but it would be interesting to expand the database so as to include more countries over a longer time period and, particularly, to analyze the impact of the policy in less developed economies, which are further away from the technological frontier. Moreover, the CPIs could be improved by including more detailed information on the enforcement features of all competition authorities and, in particular, on the sanctions that are effectively imposed on convicted firms and individuals and on the resources employed and the number of cases investigated by the EU Commission. However, such refinements of the CPIs are difficult to achieve because of the lack of available data. Indeed, if competition authorities were to increase their accountability by collecting and keeping reliable data on the enforcement of competition policy in an easily accessible format, studying the effectiveness of competition policy would become much easier.

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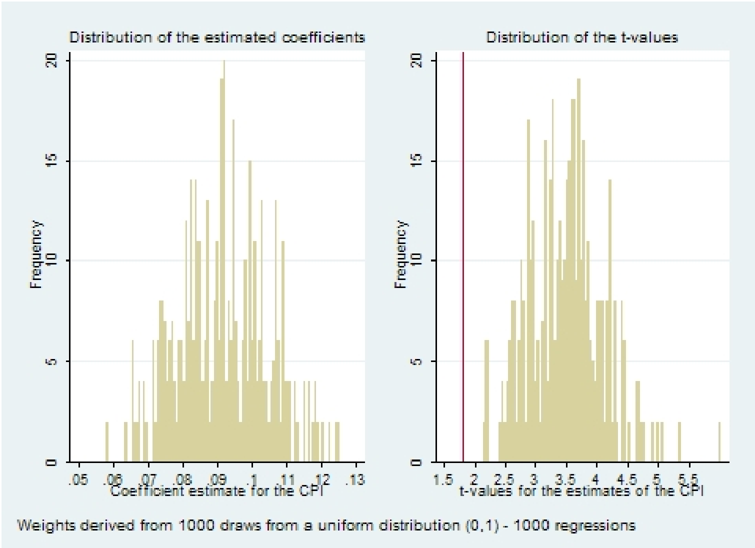
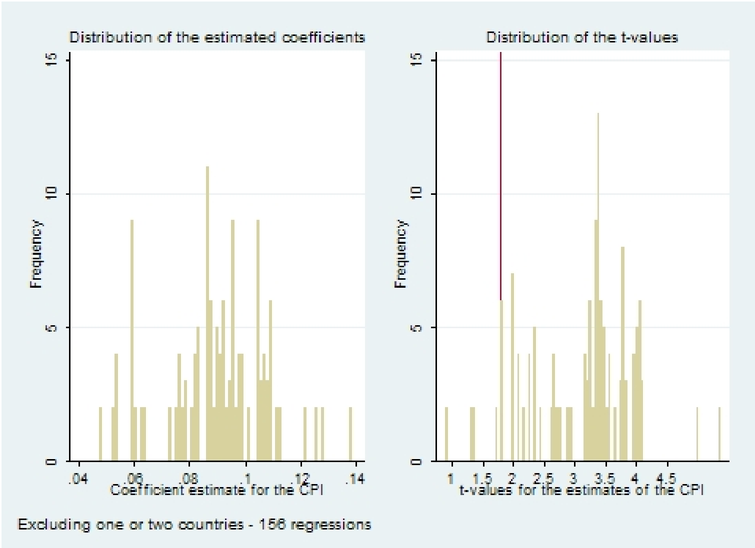
6 Figures and Tables

Figure 1: Distribution of the β Coefficients and t-statistics obtained by Random Weights



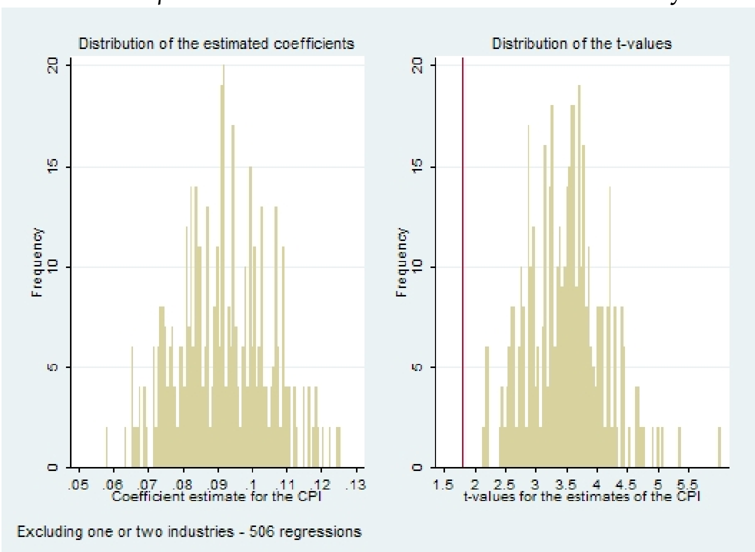
In the first panel, we represent the distribution of the estimated β coefficients from 1,000 regressions. In each of these regressions, the CPI index is built using random weights derived from a uniform distribution (0,1) and normalized to sum to 1. In the second panel, we represent the distribution of the t-statistics for the estimated coefficients. The red line represents the critical value for significance at the 10% level.

Figure 2: Distribution of the β Coefficients and t-statistics obtained by Excluding Countries



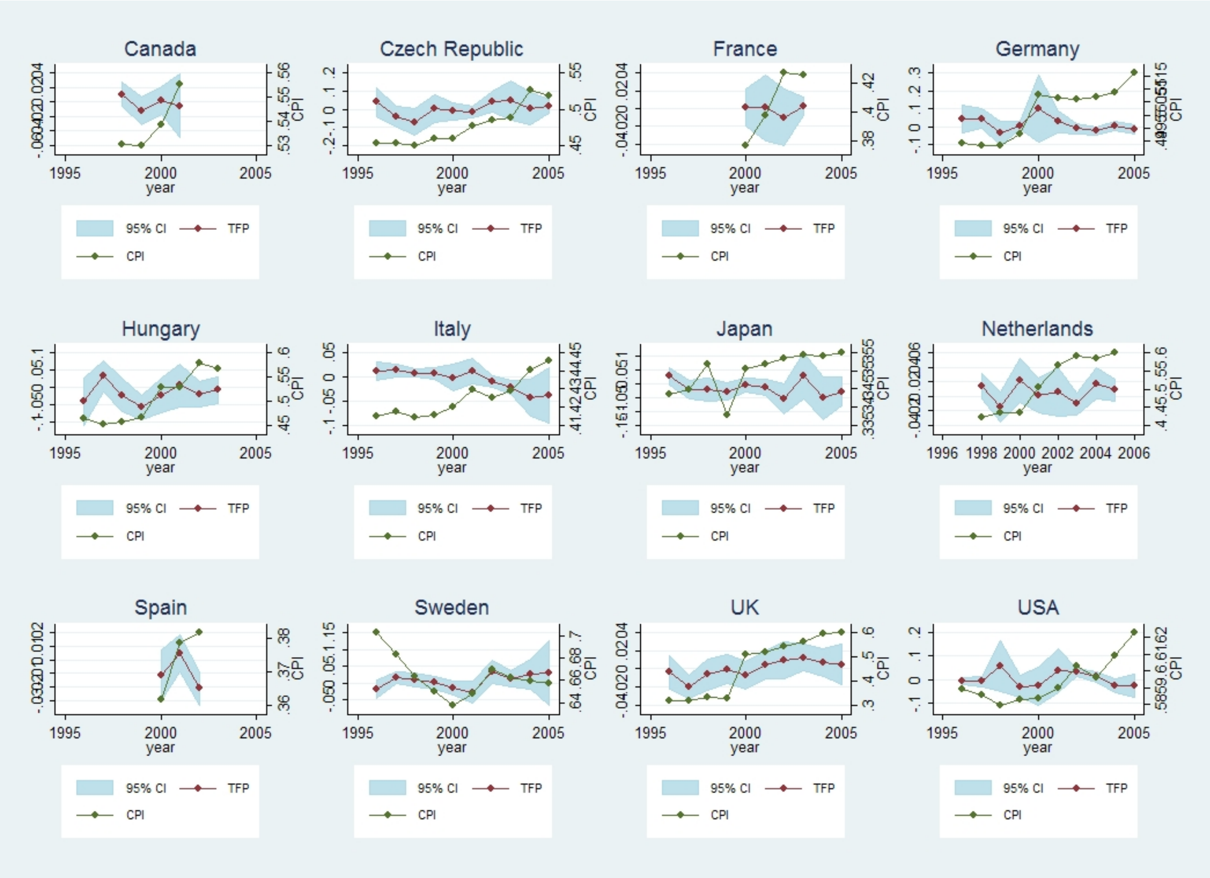
In the first panel, we represent the distribution of the estimated β coefficients from 156 regressions. In each of these regressions, we exclude one or two countries from our sample. In the second panel, we represent the distribution of the t-statistics for the estimated coefficients. The red line represents the critical value for significance at the 10% level.

Figure 3: Distribution of the β Coefficients and t-statistics obtained by Excluding Industries



In the first panel, we represent the distribution of the estimated β coefficients from 506 regressions. In each of these regressions, we exclude one or two industries from our sample. In the second panel, we represent the distribution of the t-statistics for the estimated coefficients. The red line represents the critical value for significance at the 10% level.

Figure 4: Residual TFP Growth and the CPIs



TFP growth is measured as the residual from equation (2], where we exclude the CPI from the regressors. The shaded area represents the 95% confidence interval around the mean TFP growth among the 22 industries for each country.

Table 1: Preliminary Statistics

	Obs.	Mean	St. Dev.	Min.	Max	Description
TFP Growth	1847	0.0096	0.0686	-0.2818	0.2727	TFP growth from the EU-KLEMS database
TFP Leader	1847	0.0154	0.0931	-0.7863	0.6246	Country-industry with the highest TFP value relative to a common reference point
Technology Gap (TFP)	1847	0.6891	0.6697	0	5.6063	$TFP_{Ljt} - TFP_{ijt}$
LP Growth	1847	0.0280	0.0724	-0.3238	0.5906	Growth of value added per worker
LP Leader	1847	0.0463	0.1153	-0.4899	1.2823	Country-industry with the highest LP value relative to a common reference point
Technology Gap (LP)	1847	3.0089	5.4108	0	88.0470	$LP_{Ljt} - LP_{ijt}$
R&D	1463	0.0253	0.0574	0	0.4041	Yearly industry-level R&D expenditures over industry value added
Human Capital	1783	0.1171	0.0977	0.0058	0.5588	Share of high-skilled labor employed in each country-industry in a given year
Trade openness	1847	1.0096	1.8350	0	17.2785	Yearly industry imports over industry value added
PMR	1847	1.6721	0.5227	0.9234	3.0336	OECD indicator of product market regulation
CPI	1847	0.4976	0.1019	0.3167	0.7035	Aggregate Competition Policy Index based on subjective weights
CPI (equal weights)	1847	0.4327	0.1028	0.2240	0.6773	Aggregate Competition Policy Index based on equal weights
CPI_institution	1847	0.6048	0.1114	0.3513	0.7735	Institution Competition Policy Index based on subjective weights
CPI_enforcement	1847	0.2802	0.1587	0.0499	0.7513	Enforcement Competition Policy Index based on subjective weights
CPI_antitrust	1847	0.5023	0.1032	0.3292	0.7047	Antitrust Competition Policy Index based on subjective weights
CPI_mergers	1847	0.4834	0.1137	0.1372	0.6999	Mergers Competition Policy Index based on subjective weights
Enforcement Costs	1847	22.1471	8.2423	9.4000	33.5000	Cost of enforcing contracts - World Bank Doing Business Database
Rule of Law	1847	1.4263	0.4141	0.5251	1.8801	World Bank Worldwide Governance Indicator for rule of law
Legal System	1847	8.1494	1.0655	5.5667	9.6246	Index_2 (legal system) from the Fraser Institute Database
Market regulation (per403)	1847	1.3767	1.2564	0	5.5007	Government's programmatic position: need for regulations
Economic planning (per404)	1847	0.3348	0.6229	0	2.6971	Government's programmatic position: need for economic planning
Welfare state limitation (per505)	1847	0.5264	0.5679	0	1.9637	Government's programmatic position: need of welfare state limitations

We present preliminary statistics for all used variables in the selected estimation sample.

Table 2: Basic OLS Regressions - Aggregated Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	ΔTFP	ΔTFP	ΔLP	ΔTFP	ΔTFP	ΔLP	ΔTFP
L.CPI	0.0731**		0.0629**	0.0924***		0.0756**	
	(0.0246)		(0.0208)	(0.0243)		(0.0293)	
L.CPI (equal weights)		0.0848***			0.0925***		
		(0.0253)			(0.0209)		
TFP/LP leader				0.0653**	0.0651**	0.0795**	0.0651**
				(0.0233)	(0.0233)	(0.0356)	(0.0228)
L.Techno Gap(TFP/LP)				0.0075*	0.00748*	0.0098***	-0.0017
				(0.0041)	(0.0042)	(0.0019)	(0.0060)
Industry trend				0.0445***	0.0464***	0.0609***	0.0405***
				(0.0052)	(0.0054)	(0.0068)	(0.0060)
L.Import penetration				0.0144***	0.0144***	0.0142**	0.0134***
				(0.0039)	(0.0039)	(0.0051)	(0.0040)
L.PMR				-0.0312	-0.0264	-0.0035	-0.0251
				(0.0196)	(0.0203)	(0.0064)	(0.0212)
L.CPI-low gap							0.0534
							(0.0347)
L.CPI-medium gap							0.0817**
							(0.0291)
L.CPI-high gap							0.1240***
							(0.0344)
Constant	-0.288***	0.171***	-0.347***	-0.137**	-0.151**	-0.237***	-0.124*
	(0.0140)	(0.0167)	(0.0140)	(0.0536)	(0.0527)	(0.0446)	(0.0615)
Observations	1847	1847	1847	1847	1847	1847	1847
R^2	0.250	0.251	0.248	0.269	0.269	0.285	0.275

In columns 1,2,4,5, and 7 the dependent variable is TFP growth corrected for mark-ups. In columns 3 and 6 the dependent variable is LP growth. Standard errors in parentheses are robust and allow for correlation among industries in the same country. In all regressions we insert country-industry dummies and time dummies. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

Table 3: OLS Regressions - Dissagregated Indexes

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
TFP leader	0.0656**	0.0659**	0.0654**	0.0653**
	(0.0233)	(0.0232)	(0.0233)	(0.0234)
Industry trend	0.0428***	0.0438***	0.0444***	0.0443***
	(0.0051)	(0.0053)	(0.0051)	(0.0054)
L.Techno Gap	0.0075*	0.0076*	0.0075*	0.0075*
	(0.0042)	(0.0042)	(0.0041)	(0.0042)
L.Import penetration	0.0142***	0.0144***	0.0144***	0.0144***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
L.PMR	-0.0304	-0.0266	-0.0336	-0.0249
	(0.0196)	(0.0250)	(0.0197)	(0.0206)
L.CPI_institution	0.0705***			
	(0.0227)			
L.CPI_enforcement		0.0400*		
		(0.0195)		
L.CPI_antirust			0.0957***	
			(0.0255)	
L.CPI_mergers				0.0744***
				(0.0221)
Constant	-0.133**	-0.117*	-0.132**	-0.143**
	(0.0551)	(0.0594)	(0.0526)	(0.0587)
R^2	0.268	0.267	0.269	0.268
Observations	1847	1847	1847	1847

The dependent variable is TFP growth corrected for mark-ups. Standard errors in parentheses are robust and allow for correlation among industries in the same country. In all regressions we insert country-industry dummies and time dummies. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

Table 4: IV Regressions - Aggregated Index

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	ΔTFP	ΔTFP	ΔTFP	ΔTFP	ΔLP	ΔLP
TFP/LP leader	0.0638***	0.0640***	0.0645***	0.0647***	0.0798***	0.0798***
	(0.0186)	(0.0186)	(0.0185)	(0.0185)	(0.0186)	(0.0186)
L.Techno Gap (TFP/LP)	0.007*	0.007*	0.007**	0.007*	0.010***	0.010***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)
Industry trend	0.0487**	0.0486**	0.0487**	0.0482**	0.0567**	0.0567**
	(0.0237)	(0.0237)	(0.0237)	(0.0237)	(0.0258)	(0.0258)
L.Import penetration	0.0146***	0.0146***	0.0145***	0.0145***	0.0184***	0.0184***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0039)	(0.0040)
L.PMR	-0.0402***	-0.0493***	-0.0272**	-0.0333*	-0.0068	-0.0094
	(0.0137)	(0.0195)	(0.0173)	(0.0184)	(0.0150)	(0.0212)
L.CPI	0.222**	0.218**			0.136	0.135
	(0.102)	(0.102)			(0.111)	(0.111)
L.CPI_equal_weights			0.134*	0.128*		
			(0.0694)	(0.0706)		
Constant	-0.118*	-0.108*	-0.0603	-0.0521	-0.0688	-0.0825
	(0.0628)	(0.0646)	(0.0426)	(0.0466)	(0.0667)	(0.0706)
First-stage F-test (CPI)	51.00	55.16	121.64	116.86	51.56	55.59
First-stage F-test (PMR)		268.56		268.56		269.43
Kleibergen-Paap Wald F statistic	51.00	50.82	121.64	112.88	51.56	51.36
Hansen J statistic	2.616 (3)	2.183 (2)	3.712 (2)	3.521 (2)	3.131 (3)	3.102 (2)
Wu-Hausman test	0.2105	0.3357	0.5311	0.7575	0.5995	0.8606
Observations	1847	1847	1847	1847	1847	1847

In columns 1,2,3, and 4 the dependent variable is TFP growth corrected for mark-ups. In columns 5 and 6 the dependent variable is LP growth. Standard errors in parentheses are robust and allow for correlation among industries in the same country. The instruments are: coal, per108, per403, per404, per505. In columns 1, 3, and 5 only the CPI is instrumented, wile in columns 2, 4 and 6 both CPI and PMR are instrumented. The value of the F-statistic for the test of excluded instruments in the first-stage regressions is reported. The Sargan statistic is distributed as a χ^2 and the degrees of freedom parameters are in parentheses. We report the p-value for the Wu-Hausman F-Statistic. In all regressions we insert country-industry dummies and time dummies. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

Table 5: First-Stage Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specific.	1	2	3	4	2 & 4	5	6	6
Dep. Var.	CPI	CPI	CPI_equal	CPI_equal	PMR	CPI	CPI	PMR
L.per108	0.1292***	0.0124***	0.00940***	0.00880***	-0.0071**	0.00851***	0.00776***	-0.00636**
	(0.0013)	(0.0013)	(0.00111)	(0.00113)	(0.0030)	(0.00117)	(0.00121)	(0.00284)
L.per403	-0.0083***	-0.0126***	-0.00988***	-0.0147***	0.0578***	-0.00787***	-0.0137***	0.0678***
	(0.0015)	(0.0014)	(0.00131)	(0.00123) (0.0033)	(0.00138)	(0.00131)	(0.00308)	
L.per404	0.0060**	0.0034	0.00880***	0.00586**	-0.0353***	0.0108***	0.00724**	-0.0440***
	(0.0030)	(0.0054)	(0.00263)	(0.00268)	(0.0072)	(0.00278)	(0.00285)	(0.00671)
L.per505	0.0011	0.0191***	-0.0139***	0.00615**	0.2404***	0.00438	0.0287***	0.270***
	(0.0039)	(0.0031)	(0.00351)	(0.00280)	(0.0075)	(0.00372)	(0.00298)	(0.00703)
Partial R^2	0.1148	0.1229	0.2362	0.2290	0.4056	0.1153	0.1150	0.3780
Observations	1847	1847	1847	1847	1847	1847	1847	1847

The dependent variable is CPI in columns 1, 2, 7, and 8, CPI equal weights in columns 4 and 5, and PMR in columns 3, 6, and 9. In column 1 and 4 only the CPI/CPI equal weights is instrumented, wile in columns 2-3, 5-6, and 8-9 both the CPI/CPI equal weights and PMR are simultaneously instrumented. The Partial R-squared of excluded instruments and the value of the F-statistic for the test of excluded instruments in the first-stage regressions is reported. In all regressions we insert country-industry dummies and time dummies, as well as all the other exogenous variables from the main regression. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

Table 6: Interactions Regressions

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Enforcement Cost	-0.0100***		-0.0063**			
	(0.0007)		(0.0027)			
Rule of law	0.0211			0.0471		
	(0.0298)			(0.0391)		
Legal system	0.0115*				0.0137*	
	(0.0059)				0.0069	
L.CPI	0.0830***					
	(0.0204)					
L.CPI_LOe		0.0881***				
		(0.0143)				
L.CPI_LOg		0.182***				
		(0.0324)				
L.CPI_LOf		0.0206				
		(0.0406)				
L.CPI_LOn		0.263**				
		(0.117)				
L.CPI_lEC			0.240*			
			(0.122)			
L.CPI_mEC			0.110***			
			(0.0256)			
L.CPI_hEC			0.0938**			
			(0.0368)			
L.CPI_lRL				0.0837**		
				(0.0310)		
L.CPI_mRL				0.0945***		
				(0.0197)		
L.CPI_hRL				0.117**		
				(0.0532)		
L.CPI_lLS					0.0553	
					(0.0406)	
L.CPI_mLS					0.0722***	
					(0.0253)	
L.CPI_hLS					0.0830***	
					(0.0255)	
L.CPI_service						0.0091
						(0.0501)
L.CPI_manifacturing						0.143***
						(0.0420)
L.PMR_service						-0.0485**
						(0.0189)
L.PMR_manifacturing						-0.0235
						(0.0188)
R^2	0.273	0.270	0.271	0.270	0.270	0.272
Observations	1847	1847	1847	1847	1847	1847

The dependent variable is TFP growth corrected for mark-ups. Standard errors in parentheses are robust and allow for correlation among industries in the same country. In all regressions we insert country-industry dummies and time dummies. We control for the following variables 'TFP leader', 'Techno Gap', 'Industry trend', 'PMR', 'Import penetration' and a constant term but we do not report the coefficient estimates for space limitation and as they are comparable with those reported in Table 2. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

Table 7: Robustness Checks

	(1) (OLS) FA	(2) (OLS) EU	(3) (OLS) Non correct	(4) (OLS) Long run I	(5) (OLS) Long run II	(6) (OLS) Long run III	(7) (OLS) Aggregated
TFP/LP leader	0.0657**	0.0655**	0.0372	0.0734**	0.0842	0.0185	0.2174**
	(0.0232)	(0.0234)	(0.0340)	(0.0248)	(0.272)	(0.139)	(0.0990)
L.Techno Gap	0.0075*	0.0075*	0.0564***	-0.0027	0.0672**	-0.0070	0.0013
	(0.0041)	(0.0042)	(0.0177)	(0.0056)	(0.0286)	(0.0152)	(0.0063)
Industry trend	0.0426***	0.0450***	0.0533***	0.0548***	0.0078	0.0051**	0.2531**
	(0.0050)	(0.0055)	(0.0057)	(0.0043)	(0.0265)	(0.0020)	(0.1025)
L.PMR	-0.0315	-0.0277	-0.0141	0.00642	-0.171	-0.0406	-0.0125**
	(0.0200)	(0.0204)	(0.0213)	(0.0353)	(0.0969)	(0.0377)	(0.0058)
L.Import penetration	0.0143***	0.0143***	0.0183***	0.00792	0.0812	0.0050*	0.0044
	(0.0040)	(0.0039)	(0.0052)	(0.0051)	(0.0506)	(0.0027)	(0.0041)
L.CPI	0.0726**	0.115***	0.0662*	0.0792*	0.332*	0.0903*	0.0417*
	(0.0235)	(0.0369)	(0.0304)	(0.0397)	(0.156)	(0.0480)	(0.0236)
Constant	-0.126**	-0.152**	-0.233***	-0.230***	0.0359	0.0403	-0.0024
	(0.0546)	(0.0601)	(0.0430)	(0.0628)	(0.182)	(0.0679)	(0.0135)
R^2	0.268	0.268	0.274	0.301	0.414	0.394	0.272
Observations	1847	1847	1850	1275	1479	802	93

In all specifications we control for country-industry and time fixed-effects. In columns 1, 2, 3, 5, 6, 7, 8, and 9 the dependent variable is TFP growth corrected for mark-ups. In column 4 the dependent variable is TFP growth non-corrected for mark-ups. Column 1 and 2 report results for the model where the Aggregate CPI is constructed on the base of equal weights and the weights obtained by factor analysis (FA), respectively. Column 3 reports results for the model where the Aggregate CPI for EU member states incorporates information about EU competition policy. Column 4 reports results where all productivity measures are based on TFP non-corrected for mark-ups. Column 5 reports results where the technology gap and the productivity level of the country at the frontier are based on labor productivity. Column 6 reports results where all explanatory variables are lagged three years instead of one. Column 7 reports results based on a three-year time horizon; the explanatory variables are measured at the beginning of the period. Column 8 reports results based on a three-year time horizon; all variables are three-years averages. In this last specification, given the lack of degree of freedom, we use 12 country and 22 industry fixed effects, instead of 264 country-industry fixed-effects. Column 9 reports results based on country level observations; all industry variable are averaged using the industry value added as a weight. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

On-line Supplement to the Paper "Competition Policy and Productivity Growth: An Empirical Assessment"

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1 Introduction

In this web appendix we provide additional material on the data used in the paper, the construction of key variables, as well as additional regressions.

The first section deals with the the variables' description. We first provide additional information on our main explanatory variables, the CPIs. We then discuss in depth the construction of the TFP measure and the other variables based on it. We finally describe the additional control variables and our instruments, providing details on the sources where the data can be retrieved.

The second section presents additional regressions. We start with the discussion of alternative assumptions on the error term. We then provide further regressions using different non-linear functions of the Aggregate CPIs and additional sets of control variables. We conclude by providing results for the IV specification based on a second set of instruments.

2 Data Description

2.1 The Indexes

The Competition Policy Indexes, CPIs, incorporate data on how the key features of a competition policy regime score against a benchmark of generally-agreed best practices and summarizes them.[1] The CPIs have a pyramidal structure which encompasses a large number of sub-indicators that are progressively linearly combined using a set of weights at each level of aggregation. This structure is described in Tables A1, A2 and A3.

Table A1 shows the content of low-level indexes. The weights used to sum the information contained in each index are indicated in brackets.

Table A2 shows the eight medium-level indexes, which are given by the weighted average of the relevant low-level indexes. The weights are indicated in brackets.

Table A3 shows the different CPIs we built and the weights (in brackets) used in the aggregation process.

We now turn to the values of the Aggregate CPIs for the countries in our sample over the

[1] An even more in depth description of these indexes can be found in Buccirossi et al. (2011).

Table A1. The Low-level Indexes

Abuses	Hard-core Cartels	Other agreements	Mergers
Independence: *Nature of prosecutor (1/2)* *Nature of adjudicator and role of government (1/2)*	Independence: *Nature of prosecutor (1/2)* *Nature of adjudicator and role of government (1/2)*	Independence: *Nature of prosecutor (1/2)* *Nature of adjudicator and role of government (1/2)*	Independence: *Nature of bodies involved in Phase 1 and 2 (1/2)* *Role of government in decision (1/2)*
Separation of powers: *Separation between adjudicator and prosecutor (2/3)* *Nature of appeal court (1/3)*	Separation of powers: *Separation between adjudicator and prosecutor (2/3)* *Nature of appeal court (1/3)*	Separation of powers: *Separation between adjudicator and prosecutor (2/3)* *Nature of appeal court (1/3)*	Separation of powers: *Separation between adjudicator and prosecutor (1/3)* *Separation between Phase 1 and 2 (1/3)* *Nature of appeal court (1/3)*
Quality of the law: *Standard of proof for predation and goals that inform decision (1/2)* *Standard of proof for refusal to deal and goals that inform decision (1/2)*	Quality of the law: *Standard of proof and goals that inform decision (1/2)* *Leniency program (1/2)*	Quality of the law: *Standard of proof for exclusive contracts and goals that inform decision*	Quality of the law: *Obligation to notify (1/2)* *Efficiency clause (1/2)*
Powers during investigation: *Combination of powers (3/4)* *Availability of interim measures (1/4)*	Powers during investigation: *Combination of powers*	Powers during investigation: *Combination of powers (3/4)* *Availability of interim measures (1/4)*	
Sanction policy and damages: *Sanctions to firms (1/3)* *Sanctions to individuals (1/3)* *Private actions (1/3)*	Sanction policy and damages: *Sanctions to firms (1/3)* *Sanctions to individuals (1/3)* *Private actions (1/3)*	Sanction policy and damages: *Sanctions to firms (1/3)* *Sanctions to individuals (1/3)* *Private actions (1/3)*	
Resources: *Budget (1/2)* *Staff (1/4)* *Staff skills (1/4)*	Resources: *Budget (1/2)* *Staff (1/4)* *Staff skills (1/4)*	Resources: *Budget (1/2)* *Staff (1/4)* *Staff skills (1/4)*	Resources: *Budget (1/2)* *Staff (1/4)* *Staff skills (1/4)*
	Sanctions and cases: *Number of cases opened (1/3)* *Max jail term imposed (2/3)*		Cases: *Number of mergers examined*

period 1995–2005. Figures 1 to 3 give a general idea of the measure of the deterrence properties of the competition policy in those countries and of the relevant changes which occurred over time. It is evident from them that there is substantial cross-sectional and cross-time variation. It should be stressed that the institutional component of the aggregate index takes a greater weight (2/3), hence the evolution of the Aggregate CPIs is mostly explained by the institutional features of the competition policy which is relatively stable.[2]

To allow a clearer interpretation of the results we include only a limited number of countries

[2]The enforcement features undergo more frequent changes and so do the Enforcement CPIs. For the sake of space we have only shown the values of Aggregate CPIs. For more details on the values of the other CPIs refer to Buccirossi et al. (2011).

Table A2. The medium-level Indexes

	Abuses	Hard-core Cartels	Other agreements	Mergers
Institutional features	*Independence* (1/6) *Separation of powers* (1/6) *Quality of the law (1/6)* *Powers during investigation* (1/6) *Sanctions and damages* (1/3)	*Independence* (1/6) *Separation of powers* (1/6) *Quality of the law (1/6)* *Powers during investigation* (1/6) *Sanctions and damages* (1/3)	*Independence* (1/6) *Separation of powers* (1/6) *Quality of the law (1/6)* *Powers during investigation* (1/6) *Sanctions and damages* (1/3)	*Independence* (1/6) *Separation of powers* (1/3) *Quality of the law* (1/3)
Enforcement features	*Resources*	*Resources* (2/3) *Cases* (1/3)	*Resources*	*Resources* (2/3) *Cases* (1/3)

Table A3. The CPIs

The Aggregate CPI				
	The Antitrust CPI (3/4)			**The Merger CPI (1/4)**
	Hard-core Cartels (1/3)	**Abuses (1/3)**	**Other agreements (1/3)**	
Institutional CPI (2/3)	*Institutional features of hard core cartels*	*Institutional features of abuses*	*Institutional features of other agreements*	*Institutional features of hard core cartels*
Enforcement CPI (1/3)	*Enforcement features of hard core cartels*	*Enforcement features of abuses*	*Enforcement features of other agreements*	*Enforcement features of hard core cartels*

in each figure. Yet, to allow readers to easily perform comparisons among them, we report the sample average in each figure. Figure 1 shows the Institutional CPIs for the three OECD countries in our sample that are not part of the EU: Canada, Japan, and the US.

As a starting point, the sample average of the aggregate CPIs shows an upward trend during the sample period, which is common to almost all the 12 countries. Moreover, the time variation of the average index is significant with an average increase of almost 2% points per year (18% over the sample period). The Aggregate CPIs of the non-EU countries changed more or less markedly over the period under exam, and their levels differ considerably among each other. The aggregate CPI for the US takes very high values which are constantly among the highest in the sample, ranging between 0.58 and 0.62, therefore showing a significant time

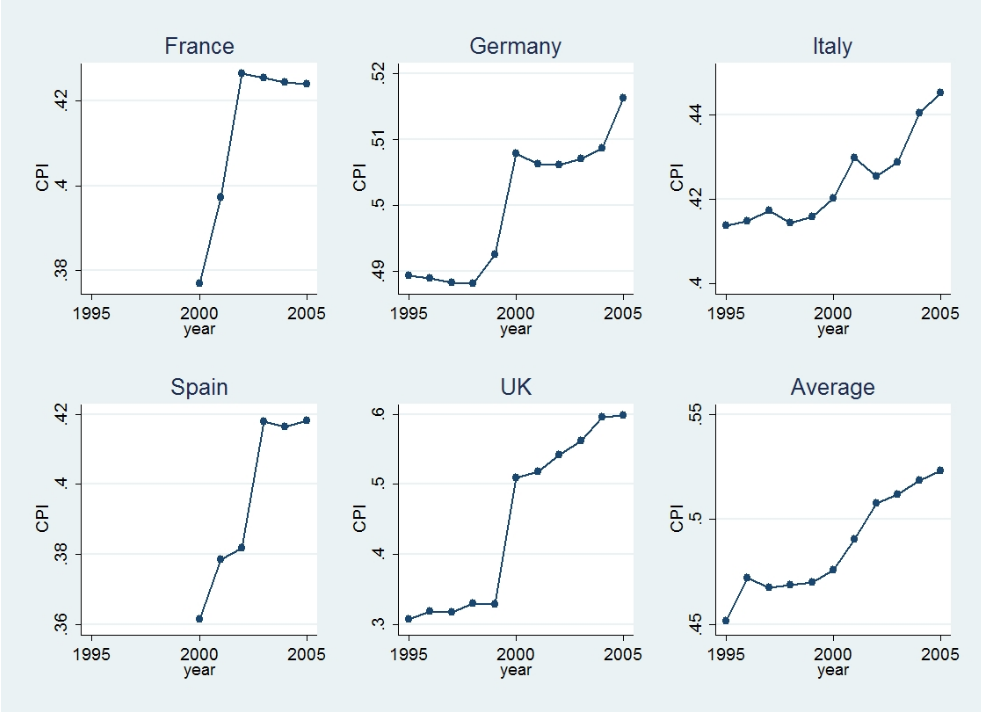
Figure 1: Aggregated CPI for the Non-EU Countries

variation. The values for Canada are also quite high (between 0.53 and 0.56) and above the sample average. The range of variation is however limited to some percentage points per year. Japan's values are very low and among the lowest in the sample for the entire period (between 0.34 and 0.35). Differently from most other countries, also the changes in the Aggregate CPI are lower than an average of 1% per year. The reason behind Japan's low performance is manifold. First, Japan suffers from the lack of a leniency program for cartel whistleblowers. Second, in Japan there is no separation between the body that prosecutes violators of the antitrust law and the body that adjudicates such cases. Third, the Japanese competition authority has limited human and financial resources. Further elements are the absence of the possibility to start a class action and the fact that the Japanese competition legislation envisages the consideration of non strictly-economic goals when assessing the effects of abuses of dominance.

Figure 2 depicts the Aggregate CPIs for the large EU member states in our sample: France, Germany, Italy, Spain, and the UK.

The first noticeable element in this figure is that the data for the first five years in the sample

Figure 2: Aggregated CPI for the Large EU Countries

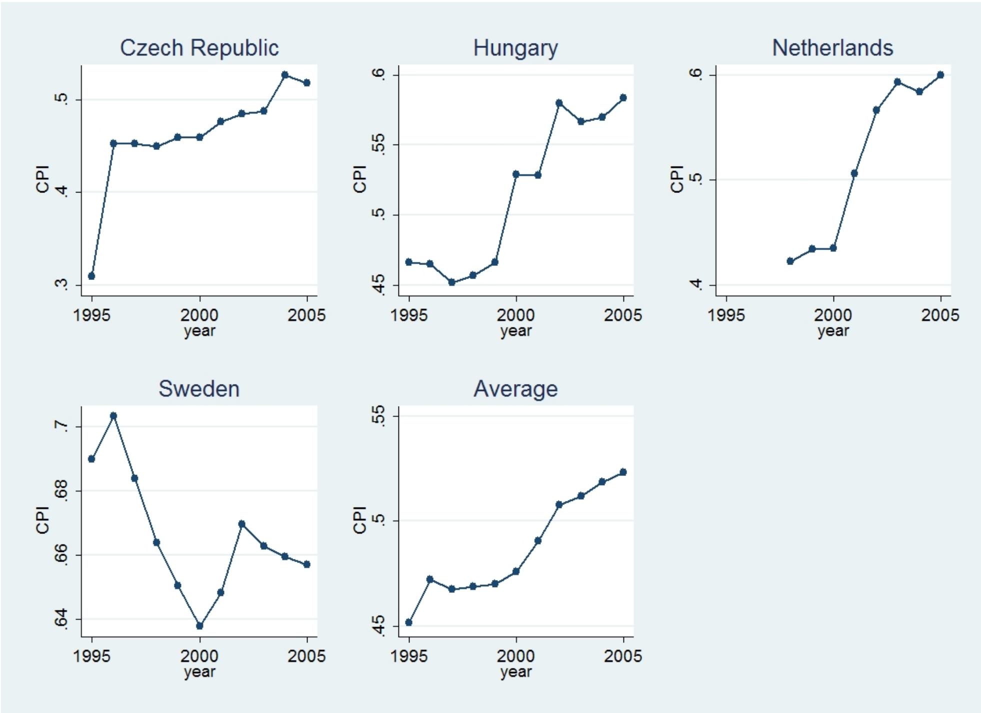


are missing for Spain and France. This lack of information does not allow one to have a clear picture of the trend for these two jurisdictions. Anyhow, the Aggregate CPIs for these two countries, as well as for Italy, are very low and consistently below the sample average (0.38–0.42 for France, 0.36–0.42 for Spain, and 0.41–0.44 for Italy). Both Spain and France experience a substantial improvement between 2000 and 2003. The former benefited from the introduction of class action in 2001 and of the powers to investigate business premises in 2003. In the latter, the quality of the institutional CPI improved because of the introduction of a leniency program for cartel whistleblowers and of the obligation to notify mergers. Germany shows a good and constant performance ranging between 0.49 and 0.52. Notably, the CPIs for the UK start well below all the values of the CPIs of the other countries (0.3), but over time they become the highest in the group (0.6). This is due to the dramatic institutional changes that accompanied the introduction of the Competition Act in 2000, coupled with a steady increase in the financial and human resources of the two competition authorities.

Figure 3 depicts the Aggregate CPIs for the small EU member states in our sample: the

Czech Republic, Hungary, the Netherlands, and Sweden.

Figure 3: Aggregated CPI for the Small EU Countries



Sweden is consistently the country with the highest CPI value, not just in this group but in the whole sample, yet this slowly declines over time (from 0.7 to 0.66) because of a reduction, in real terms, of the financial and human resources available to its competition authority. Instead, the CPIs for the other jurisdictions start below the sample average, but they all improve over time. The Czech Republic experiences a first, considerable shift in 1996, due to the competition authority acquiring independence from the government – previously all decisions were taken by a ministerial department. A further improvement takes place in 2004, when the power to investigate business premises was introduced. In the sample period, the CPI increases by 70% from a low of 0.3 to a high of 0.51. In Hungary the major changes happen in 2000, when there is an increase in the investigative powers of the competition authority and a shift in the criterion used to set the sanctions for antitrust infringements, which changed from a discretionary decision left to the adjudicator to an approach based on the firms' turnover. Moreover, in 2002 there was a substantial increase in the budget of the competition authority. These changes are captured by an increase in the CPI by over 30% from a low of 0.45 to a high of 0.59. The Netherlands did not have a competition authority before 1998. Hence, it was not possible to calculate a CPI until that year. In subsequent years, the index steadily rises by almost 50% over the sample period from a low of 0.4 to a high of 0.6 as a consequence of a regular increase in the amount and in the quality of its competition authority's resources.

These three figures give a general idea of the factors that affect the ability of a competition policy regime to deter anti-competitive behavior in the jurisdictions included in our sample and of how these have changed over time. It is evident from them that there is substantial cross-sectional and cross-time variation.

Table A4 instead shows the ranking of the 12 countries in our sample based on the average value of their Aggregate CPIs over the years 1995 to 2005 and on its value in 2005. Sweden and the US are the best-scoring countries and this is true for each year in the sample, similarly France, Spain, and Japan constantly have the lowest scores. The UK and Canada are the countries that experience the most marked change.

Table A4 : The Ranking of the Countries on the Basis of the Aggregate CPIs

Country	Ranking based on average score	Ranking based on 2005 score
Sweden	1	1
US	2	2
Canada	3	6
Netherlands	4	3
Hungary	5	5
Germany	6	8
Czech Republic	7	7
UK	8	4
Spain	9	11
Italy	10	9
France	11	10
Japan	12	12

2.2 The TFP Measures

TFP growth. The measure of TFP growth employed in our regressions is taken from the EU-KLEMS database.[3] The database improves substantially on the existing industry level databases, among which the OECD STAN database and its predecessor the ISDB database. The main limitation of previously existing databases is that they provide industry-level series on output, aggregate hours worked and aggregate capital stock, ignoring changes in the composition of factor inputs. As a result, TFP measures based on these aggregate quantities might be biased. On the contrary, the KLEMS database takes into account changes in the composition of the labor force over time. Furthermore, it discriminates among different types of capital input measures.

The TFP measure reported by the KLEMS database and employed in our regressions is based on the growth accounting methodology, which essentially consists of decomposing output growth into the contribution of input growth (labor and capital) and TFP growth.[4] TFP measures within the growth accounting framework are based on several assumptions: in particular, it is assumed that markets are perfectly competitive and that inputs are fully utilized. Under these assumptions, TFP growth can be written as follows:

$$\Delta TFP_{ijt} = ln(\frac{Y_{ijt}}{Y_{ijt-1}}) - \frac{1}{2}(\alpha_{ijt} + \alpha_{ijt-1})ln(\frac{L_{ijt}}{L_{ijt-1}}) - (1 - \frac{1}{2}(\alpha_{ijt} + \alpha_{ijt-1}))ln(\frac{K_{ijt}}{K_{ijt-1}}) \quad (1)$$

where Y_{ijt} is the real value added, L_{ijt} measures the labor input and the K_{ijt} capital input. Within the EU-KLEMS database, accurate measures of labor and capital input are based on the breakdown of aggregate hours worked and aggregate capital stock into various components. Hours worked are cross-classified by various categories to account for differences in the productivity of various labor types, such as high- versus low-skilled labor. Similarly, capital stock measures are broken down into stocks of different asset types.[5] The term α_{ijt} measures the

[3]The EU-KLEMS database is the result of a research project funded by the European Commission that involves major national level economic and statistical research centers. Details about the EU-KLEMS project can be found at the website: www.euklems.net. An overview of the methodology employed to collect data and build the measures of productivity can be found in Timmer et al. (2007).

[4]The growth accounting methodology for computing productivity has a long-standing history. For a full description of the methodology see Jorgenson et al. (1967, 2005) and Caves (1982a).

[5]The EU-KLEMS database covers all the countries involved in our study except for Canada. For measuring

labor share in value added. For our study, given that we measure the effectiveness of competition policy in promoting competition and ultimately efficiency, the main concern related to the TFP measure reported in the EU-KLEMS database is the assumption of perfect competition in the product markets. In order to take the existence of imperfectly competitive product markets into account, we modify the expression in equation (1) and multiply the labor share by industry-specific mark-ups.[6]

We estimate industry level mark-ups as in Griffith and Harrison (2004), using the following equation:

$$Markup_{ijt} = \frac{ValueAdded_{ijt}}{LaborCosts_{ijt} + CapitalCosts_{ijt}} \tag{2}$$

where $ValueAdded_{ijt}$ is nominal value added, Labor Costs is labor compensation and Capital Costs is capital compensation.[7] The main source of data for computing mark-ups is still the EU-KLEMS database.[8] An important aspect to notice is that the measure of capital input necessary to compute capital costs is a somewhat cruder measure than the one employed in the construction of the TFP measure. In particular, we use an aggregate measure of capital stock, not accounting for different types of capital assets.[9] This capital stock measure is computed starting from the real gross fixed-capital formation series available in the EU-KLEMS database, using the perpetual inventory method.

Technology gap. One of the main regressors in our specifications is the technology gap between a country-industry in a given year and the technological frontier. There are several ways which can potentially be used to measure the technology gap. In our study, we follow the existing literature and use the TFP level to compute the distance to the technological fron-

TFP growth for Canada, we use data from the Groningen Growth and Development Centre (GGDC). The GGDC methodology is totally analogous to the one adopted by the EU-KLEMS consortium, of which the GGDC is a member. The correlation between the EU-KLEMS TFP and the GGDC TFP is high (0.7) and strongly significant. However, we run specifications excluding Canada and results remain qualitatively and quantitatively unchanged.

[6] In this, we follow the existing literature that explores the determinants of TFP growth. See, for example, Griffith et al. (2004), Aghion et al. (2009) and Nicoletti and Scarpetta (2003).

[7] The Capital Costs measure is obtained by multiplying the capital stock for the user cost of capital, which takes into account the real interest rate and the extent of capital depreciation. For details see Griffith et al. (2006).

[8] For the computation of capital costs, we needed data on the inflation rate, as well as on the yield on 10-years Federal Reserve Bonds. These come from the OECD MEI (Main Economic Indicators) database.

[9] The reason why we use an aggregate measure of the capital stock is that the series on gross fixed-capital formation disaggregated for different types of assets are publicly available in the EU-KLEMS database only for a limited number of countries.

tier.[10] The computation of the technology gap is made in two steps. The first step consists of evaluating the level of TFP in each country-industry relative to a common reference point – the geometric mean of the TFPs of all other countries in the same industry. This measure of the TFP level with respect to the average is given by:

$$TFP_{ijt} = ln(\frac{Y_{ijt}}{\overline{Y}_{jt}}) - \widetilde{\sigma}_{ijt} ln(\frac{L_{ijt}}{\overline{L}_{jt}}) - (1 - \widetilde{\sigma}_{ijt}) ln(\frac{K_{ijt}}{\overline{K}_{jt}})$$

where the output and input measures are the same employed in the measurement of TFP growth, and the bar denotes a geometric mean.[11] The variable $\widetilde{\sigma}_{ijt} = \frac{1}{2}(\alpha_{ijt} + \overline{\alpha}_{jt})$ is the average of the labor share in country i and the geometric mean labor share. The technology leader is defined as the country-industry with the highest value for the TFP level relative to the common reference point. The second step for computing the technology gap consists of subtracting TFP_{ijt} from TFP_{Ljt}, where the latter is the TFP level in the identified country-industry leader. Thus, the technology gap variable used in our regressions is: $TechnoGap_{ijt} = TFP_{Ljt} - TFP_{ijt}$

2.3 Other Control Variables

R&D. The variable we use in our regressions is the ratio between R&D expenditure and the industry-level value added, both in nominal values. We gathered detailed data on the level of expenditure in R&D in different industries from the OECD Analytical Business Enterprise Research and Development (ANBERD) database, which covers 19 OECD countries, from 1987 to 2004. We took data on value added from the EU-KLEMS database. Unfortunately, data on R&D for the 'Agriculture, forestry and fishing' sector and the 'Mining and quarrying' sectors for all countries involved in the study, as well as data for Hungary, are not available in ANBERD.

Human Capital. We measure human capital as the share of high-skilled labor employed in each country-industry in a given year. We took data on human capital from the KLEMS database, which holds information on the level of educational attainment of workers by industry for all the EU member countries, the US and Japan from 1970 to 2004. Unfortunately, data on human capital are not available for Canada.

[10] We employ a similar procedure to construct the technology gap based on labor productivity.

[11] Data are aggregated using national level purchasing power parities (PPPs). For the base year we use for measuring real variables (2000), neither industry-level PPPs for value added nor capital specific PPPs are available.

Trade openness. We measure the degree of openness to trade by the ratio of industry import over value added in each specific industry. The data is collected from the OECD STAN database, which contains data on total exports and imports for 19 OECD countries, plus the EU, from 1987 to 2004, disaggregated by industry.

Product Market Regulation. We measure the tightness of product market regulation by the aggregate PMR index, taken from the OECD PMR database. The aggregate PMR index covers formal regulations in the following areas: state control of business enterprizes, legal and administrative barriers to entrepreneurship, and barriers to international trade and investment. The tightness of regulation is measured at the national level on a scale between 0 and 6, where lower values indicate less tight regulation. Data on PMR are available for two years: 1998 and 2003.[12]

Quality of Institutions. The quality of the institutions of a country enters in our regressions both as a control variable and as an interaction with the CPIs in order to explore non-linearities in the effectiveness of competition policy. We use variables from four different sources to proxy the quality of the national institutions.

The first source of data is the World Bank Worldwide Governance Indicators (WGI) database, which collects aggregate and individual indicators for six dimensions of governance: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, control of corruption.[13] The data cover 212 countries and territories over the period 1996-2006 and are based on the views of a large number of enterprisers, citizens, and experts. We use the index that measures the national rule of law, as the most appropriate indicator of a country's legal system. The index takes values from -2.5 to 2.5, with higher values indicating better governance outcomes.

The second source of data is the Fraser Institute Database, which is used to construct the 'Economic Freedom of the World' indexes. From this database, we use an aggregate index (index_2) called 'legal system', which aggregates information on variables measuring judiciary independence, impartiality of the courts, protection of intellectual property, law and order, and

[12] We assume regulation before 1998 to be as tight as in 1998, and regulation after 2003 to be as tight as in 2003. For the period between 1998 and 2003 we impute an average between the two available observations.

[13] Note that all these indexes are highly correlated and, therefore, contain very similar information.

legal enforcement of contracts. These indexes, just like the WGIs, are based on the perceptions of enterprisers, citizens and experts. The indexes take values between 0 and 10, with higher values indicating better governance outcomes.

The third source of data is the Doing Business database of the World Bank and the International Finance Corporation, which collects data representing 'objective measures' of the overall quality of the regulatory and institutional environment in 181 countries. The data we use in our empirical model relate to the time and cost of enforcing debt contracts through the national courts system.[14] Finally, we use the legal origins dummies from La Porta et al. (1997).

Industry-level deviations from the trend. We use country-industry deviations from a linear and a quadratic trend to account for the effect of business cycles on TFP. When capacity is constrained, TFP growth may in fact reflect short-run demand fluctuations. We measure a different deviation from the trend for each country-industry using value added taken from the EU-KLEMS database.

2.4 Instruments for Policy

In our IV regressions we use two different sets of instruments for the policies (competition policy and PMR). First, we use political variables which are derived from the dataset developed by Cusack and Fuchs (2002) which uses two main sources:[15] the first is a database on political parties' programmatic position developed in the Manifesto dataset by Klingemann et al. (2006), while the second is the database developed by Woldendorp, Keman, and Budge (2000) on government compositions for 48 countries from 1948 onwards. For each country and year in our sample, we create measures of a government location along the Manifestos political dimensions by taking a weighted average of the programmatic positions of each of the parties belonging to government coalition. As weights, we used the number of each party's votes. We used the following programmatic positions:

[14] The time of enforcing debt contracts represents the estimated duration, in calendar days, between the moment of issuance of judgment and the moment the landlord repossesses the property (for the eviction case) or the creditor obtains payment (for the check collection case). The cost of enforcing contracts represents the estimated cost as a percentage of the debt involved in the contract. For a full description, see Djankov et. al (2003b). Both variables have been measured within the Doing Business Project from 2004 on. In our specifications, we use the end of sample (2005) values, and assume it represents the quality of contracts enforced for the entire sample period.

[15] We are very grateful to Tom Cusack for providing us with the original data and its update.

Market regulation (per403). This variable measures favorable mentions in the parties' programs of the need for regulations to make private enterprizes work better, actions against monopoly and trusts, in defence of consumer, and encouraging economic competition.

Economic planning (per404). This variable measures favorable mentions in the parties' programs of long-standing economic planning of a consultative or indicative nature.

Welfare state limitations planning (per505). This variable measures negative mentions in the parties' programs of the need to introduce, maintain or expand any social service or social security scheme.

European Community (per108): This variable measures favorable mentions in the parties' programs of the European Community in general, and on the desirability of expanding its competency.

Second as additional instruments for the CPI and for regulation in a given country, we use different aggregations of the level of these variables in other countries. In particular, we build different set of instruments based on country grouping (EU countries vs. non-EU countries). We then use as instruments for the policies (CPI and PMR) in one country the average value of these variables in all other countries from the same group, as well as the average value of these variables in all countries from other groups.[16]

3 Additional Robustness Checks

3.1 The Assumptions on the Error Terms

Following the existing literature (e.g. Nicoletti and Scarpetta, 2003, Grififth et al., 2004, and Bourlès et al., 2010) we specified a particular structure for the individual effects and the error term in equations (1) and (2). In this appendix, we present and discuss a large amount of specifications, which are aimed at testing the robustness of our assumptions along two lines. First, since our data have a nested structure, as an industry is 'naturally' nested within a country, we follow Baltagi et al. (2001) and estimate several mixed-models to fit two-way, multilevel effects by maximum likelihood. Second, we more carefully analyze the autocorrelation structure of

[16]Moreover, we also try using alternative instruments, such as the US policies as instruments for EU countries, the mean policies of EU member states (including the EC) as instruments for the US policies, and the mean between the EU and US policies for the policies in non-European countries such as Canada and Japan.

the residuals, to check and, eventually, correct for serial correlation in the residuals. Table A5 reports the results of our robustness checks.

We start by estimating a model with 12 country, 22 industry, and 9 time fixed-effects and cluster the standard error at the country level, which we use as a first benchmark (column 1). Then, we replicate our main specification with 264 country-industry and 9 time fixed-effects and standard error clustered at the country level (column 2). We then try a specification with country and time-industry fixed-effects (column 3). We then use three different specifications that make use of the nested structure we discussed above and which are estimated by maximum likelihood with xtmixed in Stata. First, we specify country fixed-effects by the means of country dummies and use industry-within-country random effects. We allow for a complex, unspecified covariance structure and distinctly estimate all variances-covariances (column 4). We then assume country and industry-within-country random effects. Our model now has two random-effects equations. The first is a random intercept (constant-only) at the country level, the second a random intercept at the industry-within-country level (this, by the way, is exactly the model estimated by Baltagi et al. (2001) to investigate the productivity of public capital in private production). As before, we distinctly estimate all variances-covariances (column 5). While the size of the coefficient estimates is slightly affected, its sign and significance are not. In all specifications, we do find a strong and significant impact of the Aggregate CPI on TFP growth. Notice that, if we estimate a simple random effect model with country-industry random effects and time fixed-effects, i.e. a simplified version of specification (5), we also find a coefficient estimate for the Aggregate CPI equal to 0.0550 and significant at the 1% level. However, when we run a Hausman test to verify whether the fixed or the random-effects specification should be preferred, we reject the appropriateness of the random-effects estimator.

The second robustness check concerns another aspect of the correlation structure of the residuals and, in particular, the potential existence of serial correlation. We start from our preferred fixed-effects specifications (1)-(3) with clustered standard errors at the country level. We run the Arellano and Bond (2001) test of autocorrelation of the first order.[17] The Arellano-Bond

[17]The test was originally proposed for a particular linear Generalized Method of Moments dynamic panel data estimator (Arellano and Bond, 1991), but is quite general in its applicability (more general than the xtserial test in Stata). It can be applied to linear GMM regressions in general and, thus, to the special cases of ordinary least squares

test rejects the null hypothesis in model (1) but not in model (2) and (3). Therefore, we re-estimate the basic models (1)-(3) by assuming an AR(1) structure for the error term. Results are reported in columns (6)-(8). Again, in all specifications we estimate a positive and significant coefficient for the CPI.[18] This is very similar in size to the coefficient estimated in our reference model. Eventually, the coefficients estimates are a bit larger in the models with AR(1) disturbances if compared to the basic specifications.

To conclude, while the structure for the error term that we adopted might appear to be subjective, we believe that it does not significantly affect our conclusions.

(OLS) and two-stage least-squares (2SLS). To run this test we therefore estimate the LSDV version of models (1)-(3).

[18]Notice that the TFP level of the leader was dropped from specification (8) because of collinearity.

Table 1: Table A5 - Different Specifications with Various Individual Effects and Correlation Structures

	(1) OLS	(2) OLS	(3) OLS	(4) MLE	(5) MLE	(6) OLS	(7) OLS	(8) OLS
TFP leader	0.0738***	0.0653**	0.133***	0.0869***	0.0990***	0.0728***	0.0657***	dropped
	(0.0236)	(0.0233)	(0.0370)	(0.0192)	(0.0184)	(0.0173)	(0.0219)	
L.Techno Gap	0.0072	0.0075*	0.0149	0.0050*	0.0031	0.0073**	0.0063	0.0054
	(0.0060)	(0.0041)	(0.0107)	(0.0030)	(0.0027)	(0.0030)	(0.0051)	(0.0040)
L.Import penetration	0.0047**	0.0144***	0.0048*	0.0045***	0.0046***	0.0050***	0.0172***	0.0049***
	(0.0019)	(0.0040)	(0.0022)	(0.0011)	(0.0010)	(0.0009)	(0.0050)	(0.0011)
L.PMR	-0.0328*	-0.0312	-0.0331*	-0.0334**	-0.0079*	-0.0323***	-0.0529***	-0.00419
	(0.0162)	(0.0196)	(0.0167)	(0.0132)	(0.0047)	(0.0115)	(0.0156)	(0.00352)
L.CPI	0.0868***	0.0924***	0.0832**	0.0875**	0.0540**	0.0849**	0.115**	0.0563***
	(0.0243)	(0.0243)	(0.0278)	(0.0380)	(0.0223)	(0.0410)	(0.0476)	(0.0132)
Constant	0.0472	-0.152***	0.0272	-0.0045	-0.0091	-0.0021	-0.0125	-0.0077
	(0.0328)	(0.0440)	(0.0463)	(0.0256)	(0.0161)	(0.0329)	(0.0265)	(0.0058)
Correlation Structure	Clustered	Clustered	Clustered	Unstructured	Unstructured	AR(1)	AR(1)	AR(1)
Country Effects	Fixed (12)		Fixed (11)	Fixed (12)	Random (12)	Fixed (12)		Fixed (12)
Industry Effects	Fixed (22)					Fixed (22)		
Industry-within-country Effects		Fixed (264)		Random (256)	Random (256)		Fixed (264)	
Time Effects	Fixed (9)	Fixed (9)	Fixed (9)	Fixed (9)	Fixed (9)	Fixed (9)	Fixed (9)	Fixed (9)
Industry-Time Effects			Fixed (242)					Fixed (242)
Arellano-Bond test	0.258	0.054	0.077					
LR test vs. linear regression				21.16***	18.5***			
Observations	1847	1847	1847	1847	1847	1591	1591	1628
R^2	0.121	0.269	0.255					

The dependent variable is TFP growth corrected for mark-ups. Columns 1-3 report results of the fixed-effects specifications (column 1: country, industry, time fixed-effects; column 2 country- industry and time fixed-effects; column 3 country, industry-time fixed-effects) where the error terms are robust and clustered at the country level. Column 4 reports result for a the mixed-model with country fixed-effects and industry-within-country random effects and column 5 report the results for the mixed model with country and industry-within-country random effects. In columns 4 and 5 the covariance structure is unspecified and all variances-covariances are distinctly estimated. Column 6-8 reproduce the fixed-effects specifications with clustered standard errors reported in 1-3, which are augmented to allow for an AR(1) structure in the error term. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively. The p-value of the Arellano-Bond (1991) test for AR(1) is reported.

3.2 The Non-linear Effect of Competition Policy

As we mentioned in section 2, competition policy might have a non-linear effect on productivity growth akin to the non-linear effect of competition on innovation identified in recent endogenous growth models.[19] We provide two lines of arguments to motivate why we should expect the relationship between *good* competition policy and innovation to be positive and linear.

To give an empirical support to our claims, we estimated two alternative specifications where we assume a non-linear effect of competition policy. In the first one, we use a quadratic term for the Aggregate CPI. In the second, we chose a more flexible step-wise approximation for the Aggregate CPI and separately estimate the effect of low, medium, and high values of the Aggregate CPI. Table 2 reports our results.

Column 1 reports our basic specification as a reference point. Column 2 reports the results for the quadratic specification. The linear term is negative, while the quadratic is positive and both are not significant. When we test the sum of the two coefficients (at the mean value of the policy) the overall effect is equal to 0.12 and significant at the 1% level. Moreover, over the entire range of the empirical distribution of the Aggregate CPI (from 0.31 to 0.71), we are in the increasing part of the estimated U-shaped quadratic function. The non-significance of the coefficient estimates suggests that there is no such non-linear quadratic effect of CPI on productivity growth, as the data seem to refuse such specification. In the third specification, we therefore assume a step function for the effect of the CPI, which is more general and imposes a less severe structure to the data.[20] The coefficient estimates for all the Aggregate CPI coefficients are around 0.095. However, the coefficient estimates for medium and high CPI are significant, while it is not for low values of competition policy. We test the pair-wise difference among them and none of these differences is significant. Moreover, none of the estimated step-coefficients is significantly different from our average effect of 0.0924.

[19]See also Whinston and Segal (2007) and Acemoglu and Cao (2010) for alternative models which point out to a controversial effect of competition on innovation.

[20]Similarly to other specifications with non-linear effect we define these categories based on the distribution of the Aggregate CPI. Hence, we define CPI_low according to the first 33% of the distribution, CPI_medium up to 67% of the distribution and CPI_high as the top 33% of the distribution. We also experimented with the first quartile, second and third, and fourth quartile and results were very similar.

Table 2: OLS Regressions - Non-linear Effect of Competition Policy

Specif.	(1) Basic	(2) Quadratic	(3) Step-wise
TFP leader	0.0653**	0.0654**	0.0653***
	(0.0233)	(0.0234)	(0.0240)
L.Techno Gap	0.00748*	0.00738*	0.00747
	(0.00413)	(0.00413)	(0.00562)
Industry trend	0.0445***	0.0452***	0.0446**
	(0.00518)	(0.00535)	(0.0255)
L.Import penetration	0.0144***	0.0144***	0.0144**
	(0.00396)	(0.00392)	(0.00649)
L.PMR	-0.0312	-0.0325	-0.0332**
	(0.0196)	(0.0203)	(0.0178)
L.CPI	0.0924***	-0.113	
	(0.0243)	(0.393)	
L.CPI squared		0.338	
		(0.426)	
L.CPI_low			0.102
			(0.0666)
L.CPI_medium			0.0926**
			(0.0489)
L.CPI-_igh			0.0995**
			(0.0472)
Constant	-0.137**	-0.0731	-0.137
	(0.0536)	(0.107)	(0.104)
L.CPI+L.CPI squared		0.125***	
		(0.044)	
Observations	1847	1847	1847
R^2	0.269	0.269	0.269

In columns 1,2, and 3 the dependent variable is TFP growth corrected for mark-ups. Standard errors in parentheses are robust and allow for correlation among industries in the same country. In all regressions we insert country-industry dummies and time dummies. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

3.3 Controlling for R&D and human capital

As we mentioned in section 2, there are two other important control variables – R&D and human capital – for which we unfortunately have many missing values.[21] Yet, we still want to analyze whether their introduction substantially affects our results, especially in light of potential omitted variable bias. In column 2, we therefore add R&D to our basic specification, which reduces the number of observations to 1,463. In line with Griffith et al. (2003), R&D intensity has a positive and significant impact on TFP growth. All other results, and especially the size and significance of the coefficient estimate for the Aggregate CPI, are not affected. In column 3, we report the results for our basic specification using the sub-sample where R&D is not missing. Again, our results are almost not affected. In column 4 as a further control, we add human capital to our basic specification, which reduces the observation to 1,783. Again, this variable has a positive effect on TFP growth which, however, is not statistically significant. The other results are not substantially changed. We finally introduce both R&D intensity and human capital (column 5) and run our basic regression without these controls in the sub-sample where both variables are non-missing (column 6). Again, our main results are not affected, yet now the two controls are significant. This could be due to the sample selection effect, given that we run this specification on a much smaller sub-sample (1,408 observations). From this point on, we therefore decide to use our basic specification so that we can use the maximum possible number of observations.[22]

[21] In particular, R&D data are missing for Hungary and for several industries-years in other countries, while Human Capital is missing for Canada.

[22] We do however run all regressions and robustness checks also adding R&D intensity and human capital as additional controls. These results can be obtained from the authors upon request.

Table 3: Basic OLS Regressions - Aggregated Index

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
TFP leader	0.0653**	0.0885***	0.0870***	0.0599**	0.0811***	0.0863***
	(0.0233)	(0.0251)	(0.0257)	(0.0232)	(0.0254)	(0.0259)
L.Techno Gap	0.0075*	0.0162**	0.0168**	0.0085*	0.0181**	0.0178**
	(0.0041)	(0.00706)	(0.00724)	(0.0042)	(0.0069)	(0.0072)
Industry trend	0.0445***	0.127***	0.127***	0.0369***	0.131***	0.127***
	(0.0052)	(0.0103)	(0.0100)	(0.0052)	(0.0106)	(0.0100)
L.Import penetration	0.0144***	0.0171**	0.0174**	0.0147***	0.0170**	0.0171**
	(0.0040)	(0.0056)	(0.0056)	(0.00415)	(0.0055)	(0.0056)
L.PMR	-0.0312	-0.0380**	-0.0379**	-0.0390*	-0.0506**	-0.0410**
	(0.0196)	(0.0172)	(0.0163)	(0.0205)	(0.0175)	(0.0168)
L.CPI	0.0924***	0.0827***	0.1064***	0.0945***	0.0800***	0.111***
	(0.0243)	(0.0263)	(0.0290)	(0.0221)	(0.0231)	(0.0291)
L.R&D		0.6750***			0.6633**	
		(0.1880)			(0.2131)	
L.Human Capital				0.286	0.460*	
				(0.172)	(0.218)	
Constant	-0.137**	-0.433***	-0.439***	-0.00989	0.0147	0.0205
	(0.0536)	(0.0543)	(0.0516)	(0.0240)	(0.0292)	(0.0308)
R^2	0.269	0.294	0.290	0.273	0.299	0.292
Observations	1847	1463	1463	1783	1408	1408

The dependent variable is TFP growth corrected for mark-ups. Standard errors in parentheses are robust and allow for correlation among industries in the same country. In all regressions we insert country-industry dummies and time dummies. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

3.4 The IV Regressions Using Hausman-Type Instruments

Even though the instruments proposed in section 2.2 seem to be a reasonable choice, there could still be a concern that they might be potentially correlated with other omitted factors. Therefore, we present a second set of results, based on a very different set of instruments. Following an established literature in industrial organization, we use the policies in neighboring jurisdictions as instruments for the policies in a given country. While the formulation of competition policy in a given country is likely to be affected by the evolution of competition policy in neighboring countries, the latter should not correlate with the rate of TFP growth in the country of interest. This provides the exclusion restriction necessary for identification. The existence of a correlation among policies in different countries is supported by the observable common trends in the evolution of competition policy during the last decades. These trends are possibly due to the leading policy-setting role taken by jurisdictions such as the US or the EU, after which the other jurisdictions' policies are modeled. Moreover, a vigorous international academic and policy debate established a general consensus about the most efficient policies to adopt in the field of competition laws, which surely also generate common trends in its evolution over time.[23]

Hence in table 4, we reproduce the estimates reported in table 5 of the paper but using these alternative instruments. In columns 1 and 2, we use our preferred Aggregate CPI based on our subjective weights, in columns 4 and 5, we use the Aggregate CPI based on equal weights, and in columns 5 and 6 we use labor productivity instead of total factor productivity measures. We instrument for the Aggregate CPI alone in columns 1, 3, and 5 and for both the Aggregate CPI and PMR in columns 2, 4, and 6. Again, we consistently estimate a positive and mostly significant coefficient for competition policy. Similarly to the previous specifications, the instruments seem to be good in terms of correlation to the potentially endogenous variables (F-statistic for the excluded instruments), they do not seem to be weak (high value of the Kleibergen-Paap F

[23]The role of multinational cooperation for the discussion and adoption of best practices around the world increased over the years covered in our sample. Such cooperation, which took place within the OECD and other international organizations, was fostered by the creation of the International Competition Network (ICN). This informal forum was initiated by the US in 1995 with the aim of providing a platform for competition authorities from around the world to discuss the whole range of practical competition policy enforcement and policy issues. The main objective of the ICN is precisely to spread best practice and promote convergence.

statistic) while they are uncorrelated to the error terms (Hansen J statistic).[24] Moreover, also in this case the Wu-Hausman test cannot reject the null hypothesis of exogeneity, which might also partially explain the reduction in the significance level, as the IV estimates are less efficient than OLS estimates.

[24] In table 5 we report the first-stage regressions for the IV specifications 4 and 6 of table 4. The instruments are the mean of the policies in other countries from the same group (CPI_G and PMR_G) and a different group (CPI_NG and PMR_NG). While we could potentially expect a positive correlation if *all* policies move in the same direction, it is not a priori clear whether this should be expected for the mean policies over the entire sample period. Indeed, we report negative and significant average correlations.

Table 4: IV Regressions - Hausman-type of Instruments

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	ΔTFP	ΔTFP	ΔTFP	ΔTFP	ΔLP	ΔLP
TFP/LP leader	0.0636***	0.0648***	0.0633***	0.0651***	0.0814***	0.0803***
	(0.0186)	(0.0185)	(0.0186)	(0.0185)	(0.0190)	(0.0187)
L.Techno Gap (TFP/LP)	0.00736*	0.00739*	0.00737*	0.00735*	0.00992***	0.00986***
	(0.00400)	(0.00399)	(0.00400)	(0.00399)	(0.00137)	(0.00135)
Industry trend	0.0491**	0.0460*	0.0528**	0.0471**	0.0652**	0.0591**
	(0.0238)	(0.0236)	(0.0241)	(0.0236)	(0.0264)	(0.0258)
L.Import penetration	0.0147***	0.0145***	0.0147***	0.0144***	0.0190***	0.0186***
	(0.00361)	(0.00360)	(0.00361)	(0.00359)	(0.00404)	(0.00397)
L.PMR	-0.0410***	-0.0376***	-0.0287**	-0.0342***	-0.0259	-0.0118
	(0.0142)	(0.0128)	(0.0118)	(0.0128)	(0.0159)	(0.0140)
L.CPI	0.233**	0.140*			0.409***	0.214**
	(0.115)	(0.0784)			(0.129)	(0.0865)
L.CPI_equal_weights			0.213**	0.106*		
			(0.0983)	(0.0634)		
Constant	-0.124*	-0.0679	-0.102*	-0.0392	-0.244***	-0.131**
	(0.0703)	(0.0538)	(0.0565)	(0.0420)	(0.0790)	(0.0595)
First-stage F-test (CPI)	77.33	89.70	106.25	158.55	76.54	89.30
First-stage F-test (PMR)		208.45		205.03		210.94
Kleibergen-Paap Wald F statistic	77.33	89.66	106.25	151.35	76.54	89.25
Hansen J statistic	0.781 (1)	1.734 (2)	0.928 (1)	2.485 (2)	2.705 (1)	6.598 (2)
Wu-Hausman test	0.2366	0.3451	0.2270	0.2733	0.111	0.1599
Observations	1847	1847	1847	1847	1847	1847

The dependent variable in columns 1, 2, 3, 4 is TFP growth corrected for mark-ups. The dependent variable in columns 5 and 6 is labor productivity growth. Standard errors in parentheses are robust and allow for correlation among industries in the same country. The instruments in the IV regressions are the average values of CPI and PMR among the other countries in the same group (European and non-European countries) and among the other countries in a different group. In columns 1, 3, and 5 only the CPI is instrumented, while in columns 2, 4, and 6 both CPI and PMR are instrumented. The value of the F-statistic for the test of excluded instruments in the first-stage regressions is reported. The Hansen J statistic is distributed as a χ^2 and the degrees of freedom parameters are in parentheses. We report the p-value for the Wu-Hausman F-Statistic. In all regressions we insert country-industry dummies and time dummies. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

Table 5: First Stage Regressions - Hausman-type of Instruments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specific.	1	2	3	4	2 & 4	5	6	6
Dep. Var.	CPI	CPI	CPI_equal	CPI_equal	PMR	CPI	CPI	PMR
[1em] L.CPI_NG	-0.586***	-0.460***				-0.581***	-0.454***	1.091***
	(0.150)	(0.152)				(0.150)	(0.152)	(0.326)
L.CPI_G2	-0.171***	-0.154***				-0.168***	-0.150***	0.318***
	(0.0321)	(0.0315)				(0.0318)	(0.0313)	(0.0671)
L.CPIe_NG			-1.101***	-0.245*	1.451***			
			(0.153)	(0.147)	(0.348)			
L.CPIe_G2			-0.244***	-0.259***	0.366***			
			(0.0349)	(0.0315)	(0.0746)			
L.pmr_NG		-0.623***		-0.206**	-9.992***		-0.623***	-10.09***
		(0.109)		(0.103)	(0.244)		(0.109)	(0.233)
L.pmr_G2		-0.414***		-0.370***	-2.486***		-0.414***	-2.484***
		(0.0319)		(0.0286)	(0.0676)		(0.0319)	(0.0684)
Partial R^2	0.0894	0.1856	0.1189	0.2872	0.3412	0.0881	0.1841	0.4420
Observations	1847	1847	1847	1847	1847	1847	1847	1847

The dependent variable is CPI in columns 1, 2, 4, and 5 and PMR in columns 3 and 6. In column 1 and 4 only the CPI is instrumented, wile in columns 2-3 and 5-6 both CPI and PMR are simultaneously instrumented. The Partial R-squared of excluded instruments and the value of the F-statistic for the test of excluded instruments in the first-stage regressions is reported. In all regressions we insert country-industry dummies and time dummies, as well as all the other exogenous variables from the main regression. The symbols ***, **, and * represent significance at the 1%, 5%, and 10% significance respectively.

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