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Aggregate uncertainty and sectoral productivity growth: The role of credit constraints ☆

Sangyup Choi [a], Davide Furceri [b,c,*], Yi Huang [d], Prakash Loungani [b]

[a] School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, South Korea
[b] International Monetary Fund, 1900 Pennsylvania Ave NW, Washington, D.C. 20431, USA
[c] University of Palermo, Italy
[d] Graduate Institute of International and Development Studies, Maison de la Paix, Chemin Eugène-Rigot 2, 1202 Genève, Switzerland

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ABSTRACT

We show that an increase in aggregate uncertainty—measured by stock market volatility—reduces productivity growth more in industries that depend heavily on external finance. The mechanism at play is that during periods of high uncertainty, firms that are credit constrained switch the composition of investment by reducing productivity-enhancing investment—such as on ICT capital—which is more subject to liquidity risks (Aghion et al., 2010). The effect is larger during recessions, when financing constraints are more likely to be binding, than during expansions. Our statistical method—a difference-in-difference approach using productivity growth of 25 industries from 18 advanced economies over the period 1985–2010—mitigates concerns with omitted variable bias and reverse causality. The results are robust to the inclusion of other sources of interaction effects, instrumental variable approaches, and different datasets. The results also hold if economic policy uncertainty (Baker et al., 2016) is used instead of stock market volatility as a measure of aggregate uncertainty.

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1. Introduction

This paper studies the impact of uncertainty on productivity by testing a specific channel through which uncertainty can affect productivity growth: during periods of high uncertainty, firms that are credit constrained switch the composition of investment by reducing productivity-enhancing investment—such as on information and communication technology (ICT) capital—which is more subject to liquidity risks (Aghion et al., 2010). The effect is larger during recessions, when financing constraints are more likely to be binding, than during expansions. Our empirical framework is similar to Aghion et al. (2014, 2015) which respectively assess the effect of fiscal and monetary stabilization on productivity growth and how credit constraints interact with this effect.

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* Corresponding author at: International Monetary Fund, 1900 Pennsylvania Ave NW, Washington, D.C. 20431, USA.
E-mail addresses: sangyupchoi@gmail.com (S. Choi), dfurceri@imf.org (D. Furceri), yi.huang@graduateinstitute.ch (Y. Huang), ploungani@imf.org (P. Loungani).

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As Bloom (2014) notes, identifying the causal links between uncertainty and macroeconomic fluctuations using aggregate data has proved challenging. This has motivated the use of structural models or instrumental variables (IV) and 'natural experiment' approaches. For instance, Baker and Bloom (2013) use natural disasters and Durnev (2012), Julio and Yook (2012), and Gulen and Ion (2016) use elections as instruments for uncertainty. The use of industry-level data from a large number of countries over a reasonably long period offers another promising approach. Specifically, the advantages of having a three-dimensional (j industries, i countries and t time periods) dataset are twofold:

- It allows controlling for aggregate and country-sector shocks by including country-time (i,t) and country-industry (i,j) fixed effects. The former is particularly important as they allow us to control for any unobserved cross-country heterogeneity in the macroeconomic shocks that affect productivity growth. In a pure cross-country analysis, this would not be feasible, leaving open the possibility that the impact attributed to uncertainty was in fact due to other unobserved macroeconomic shocks. Moreover, the results are robust when controlling for additional factors that may affect productivity growth through external finance—such as financial depth, fiscal stabilization, and inflation.
- It mitigates concerns about reverse causality. While the direction of causality between uncertainty and productivity may be difficult to sort out at the aggregate level, it is much more likely that aggregate uncertainty affects industry-level productivity growth than the other way around. This is because, once country-time fixed effects—and therefore aggregate total factor productivity (TFP) growth—are controlled for, reverse causality implies that differences in TFP growth across sectors drive uncertainty at the aggregate level through channels different from aggregate TFP growth, which seems implausible. Moreover, our main independent variable is the interaction between uncertainty and the industry's dependence on external finance; this makes it even less plausible that causality runs from industry-level productivity growth to this composite variable. Finally, the results are robust to using economic policy uncertainty, which is less subject to reverse causality, and to IV approaches in the same vein of Baker and Bloom (2013).

A limitation of this approach is that our analysis captures the impact of uncertainty on industry-level productivity growth, rather than the aggregate effect. Inferring the impact of uncertainty on aggregate productivity growth from this micro estimate would require some additional assumptions regarding, for example, the effect of uncertainty in industries with low external finance dependence.[1]

The key finding of the paper is that the adverse impact of uncertainty on industry-level productivity growth is greater in industries that rely more on external finance. Consistent with the theoretical framework, we find that this effect is mostly driven by a reduction in the share of information technology and communications (ICT) capital in the total capital stock, rather than by a reduction in aggregate investment. In addition, the effects are larger during recessions—when financing constraints are more likely to be binding—than during expansions. These results are based on the use of data for 25 industries from 18 advanced economies over the period 1985–2010.

The paper complements previous studies looking at different channels through which uncertainty reduces productivity growth. Bloom et al. (2014) develop a structural model in which a temporary increase in uncertainty lowers aggregate output, investment, and productivity. The impact on output from an uncertainty shock in their model is sizable, a drop of three percent within one-quarter. Employment and investment fall as firms adopt a 'wait and see' attitude in the face of the increased uncertainty. TFP also drops, by about 0.5 percent within a year. In Bloom et al. (2014), this occurs because uncertainty increases the misallocation of factors across firms: "In normal times, unproductive firms contract and productive firms expand, helping to maintain high levels of aggregate productivity. But when uncertainty is high, firms reduce expansion and contraction, shutting off much of this productivity-enhancing reallocation. This slow-down in reallocation manifests itself as a fall in measured aggregate TFP."

In a related study, Lotti and Viviano (2012) consider a model with two types of workers. Those on long-term contracts are more productive but difficult to fire quickly. Workers on short-term contracts are less productive but easier to hire and fire. During periods of higher uncertainty, the ratio of short-term to long-term workers goes up as firms prefer to exploit "their current profit opportunities using less irreversible and sometimes costlier (or less efficient) inputs of production, like temporary workers, mainly in the form of employment-agency placement." The switch in the composition of the workforce lowers aggregate productivity in the face of increased uncertainty.[2] Their mechanism is analogous to ours, but we directly test the mechanism using comprehensive data on industry-level productivity growth and the share of ICT capital in the total capital stock across countries.

The rest of the paper is structured as follows. Section 2 provides a literature review. Section 3 presents the testable theoretical arguments. Section 4 discusses the data and the empirical methodology. Section 5 presents our main empirical findings and several robustness checks. Section 6 concludes.

[1] See, for instance, Stein and Stone (2013).

[2] As Lotti and Viviano (2012) note, there is ample evidence that increased use of temporary workers is associated with lower productivity, unless the hiring of such workers is accompanied by some form of training. See, for example, Michie and Sheehan (2003) for evidence from the UK; Kleinknecht et al. (2006) for the Netherlands; Dolado et al. (2012) for Spain; Cappellari et al. (2012) for Italy). Foote and Folta (2002) provide an early example of a study that claims explicitly that the low productivity of temporary workers is the cost of the real option of a lower degree of irreversibility.

2. Review of literature

Since the influential work of Bloom (2009)—which extends earlier theoretical models of Bernanke (1983) and Pindyck (1988)—there has been a revival of interest in identifying the mechanisms through which uncertainty affects the real economy.[3] Recent empirical evidence, mostly using vector-autoregression (VAR) models, tends to find a negative impact of uncertainty shocks on macroeconomic outcomes (Bloom, 2009; Bachmann et al., 2013; Gourio et al., 2013; Carrière-Swallow and Céspedes, 2013; Caggiano et al., 2014; Choi and Loungani, 2015; Leduc and Liu, 2016; Surico and Mumtaz, 2016).

We provide empirical evidence that credit constraints play an important role in shaping the effect of an increase in uncertainty on productivity growth. Our work contributes to three main strands of the literature on uncertainty and growth. The first strand of the literature has emphasized the role of financial frictions in amplifying the effect of uncertainty shocks by raising borrowing costs and reducing micro and macro growth within a general equilibrium framework (Arellano et al., 2010; Christiano et al., 2014; Gilchrist et al., 2014). Caldara et al. (2016) and Popp and Zhang (2016) further quantify the important role of financial frictions in amplifying the effect of uncertainty shocks using more sophisticated VAR models. We contribute to this strand of the literature by providing novel empirical evidence of the interaction between uncertainty and financial frictions. To the best of our knowledge, this is the first attempt to use both cross country- and sector-level data to study the macroeconomic effect of uncertainty shocks.[4]

The second strand of the literature attempts to resolve the issues of endogeneity and reverse causality between uncertainty and aggregate variables by using disaggregated data. For example, using a heterogeneous firm dynamic model calibrated to German firm-level data, Bachmann and Bayer (2013) conclude that an increase in uncertainty is an endogenous response to a negative economic condition rather than a cause. This evidence emphasizes the need for a more careful empirical design to quantify the effect of uncertainty on growth. To address reverse causality, studies in this strand of the literature have used firms' characteristics to identify the transmission channels through which uncertainty affects firm-level decisions.[5] Our paper is similar to these papers given that we use aggregate-level uncertainty, but we also exploit cross-country variation in uncertainty and cross-industry variation in financial constraints.

The third strand of the literature analyzes the relationship between volatility and long-run growth. There have been extensive efforts to identify the channels through which volatility interacts with growth (King and Levine, 1993; Ramey and Ramey, 1995; Martin and Rogers, 2000; Acemoglu et al., 2003; Imbs, 2007). However, Imbs (2007) emphasize that the sign of the relationship between volatility and growth at the aggregate level cannot be used to draw inferences on what mechanisms are supported by the data. By addressing this concern using the disaggregated data, we confirm the finding of Ramey and Ramey (1995) that the negative effect of volatility on growth mainly works through technology adoption rather than capital accumulation.

3. Theoretical argument

We provide a simple theoretical argument largely drawn from Aghion et al. (2010, 2014) to formulate the testable hypotheses of the paper. In these papers, the intuition of the model is that the precautionary motive of credit-constrained firms results in a sub-optimal level of productivity-enhancing investment when firms face uncertainty about the future aggregate economic conditions. Suppose there are two types of investment projects (long- versus short-term), where the former is riskier but more productive than the latter. One can think of the former as investment in ICT (or R&D) which is subject to liquidity risk, as a firm can make very little profits from an early termination of this type of investment. The latter is the purchase of equipment or machinery that can be used as a mode of production instantly.[6]

If a firm can borrow freely from an outside lender up to the present discounted value of its long-term project when hit by a liquidity shock (i.e., a firm is not credit constrained), it will invest in each project at the optimal scale. However, a credit-constrained firm which cannot borrow from an outside lender needs to generate its own cash flows via short-term investment to cope with liquidity risk, thus ending up investing at a sub-optimal level.

An increase in uncertainty, when it interacts with credit constraints, exacerbates this problem by discouraging constrained firms from engaging in long-term investment. This is because, with a mean-preserving spread in the distribution of a future aggregate productivity shock, long-term investment is less likely to be successful, making a constrained firm effectively risk averse.[7] However, the mean-preserving spread does not affect the decision of an unconstrained firm, thereby

[3] See Bloom (2014) for a detailed survey of these mechanisms.

[4] Although a few studies (Carrière-Swallow and Céspedes, 2013; Choi, 2016) explicitly focus on the interaction between uncertainty and financial frictions in emerging market economies, they only consider cross-country differences in the degree of financial frictions. Ghosal and Loungani (1996, 2000) study the interaction between financial frictions and uncertainty at the industry-level, but their analysis is limited to the US economy.

[5] For example, Bulan (2005) studies how firm-specific uncertainty affects firm-level investment via a real option channel using firm-level panel data of US manufacturing firms. In a similar vein, Leahy and Whited (1996), Julio and Yook (2012), Handley and Limao (2015), Gulen and Ion (2016), and Byun and Jo (2018) study how uncertainty affects firm-level investment and find that the heterogeneous effects of uncertainty shocks depending on various firm characteristics such as the cash flows, growth opportunities, size, cash holdings, costs of entry and exit, and the degree of investment irreversibility.

[6] It is important to note that the distinction does not necessarily imply a difference in the actual interval between investment decisions and production of output, although we call them long-term and short-term investment for convenience.

[7] This is because of an increase in the probability of the lower-tail realization following the mean-preserving spread that reduces a chance of surviving a liquidity shock.

increasing the difference in productivity between the two groups of firms. This channel is stronger during recessions than expansions as more firms become credit constrained during recessions.

This firm-level argument can be extended to the level of industry. An industry that heavily relies on external finance in the data can be seen as an industry with a larger share of constrained firms in the model. As a result, an increase in aggregate uncertainty reduces the share of productivity-enhancing investment more in industries that are credit constrained, thereby reducing productivity growth more in these industries, which are our main hypotheses. To the extent to which credit constraints bind more in a bad state, the interaction between an increase in uncertainty and financial constraints on the TFP growth is expected to be larger in recessions than expansions.

We empirically test these hypotheses by using industry-level international panel data on TFP growth and the ICT capital share, and by exploiting heterogeneity in the degree of external financial dependence across industries in the spirit of Rajan and Zingales (1998). Although ICT investment is not a perfect empirical proxy for the model counterpart in Aghion et al. (2010) or Aghion et al. (2014), it still allows us to identify a specific mechanism through which uncertainty interacts with credit constraints in affecting productivity growth.[8]

4. Data and methodology

4.1. Data

This section provides a description of the main variables used in the empirical analysis and discusses the choice of the database used to test the model's prediction. The analysis uses the KLEMS database instead of other alternatives, such as OECD Structural Analysis Database (STAN) or Industrial Statistics Database by United Nations Industrial Development Organization (UNIDO). The main reason is that the focus of our paper is to identify a specific channel through which uncertainty affects productivity—our model posits the asymmetric effect of an increase in uncertainty on the investment decision of credit constrained firms in productivity-enhancing activity—and the KLEMS database provides consistent measures of both the share of ICT capital in the total capital stock and the growth of TFP. Our sample covers an unbalanced panel of 25 industries from 18 advanced economies (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hungary, Korea, Ireland, Italy, Japan, the Netherlands, Spain, Sweden, the United Kingdom and the United States) over the period 1985–2010. The sample is dictated by the availability of the main variable of interest (TFP growth and the stock of ICT capital).

While other databases often used in cross-country/industry analysis, such as OECD STAN or UNIDO do not provide the estimates of TFP, the KLEMS database is explicitly designed to provide consistent estimates of TFP across countries.[9] Major advantages of KLEMS over STAN or UNIDO also include a breakdown of intermediate inputs into energy, material, and services, a breakdown of investment into various asset types, estimates of multi-factor productivity based on growth accounting.[10] The last two properties of KLEMS are essential in our empirical analysis. Although STAN provides industry-level series on output, employment, and capital stocks for OECD member countries, they are mostly based on data published in the latest vintage of the National Accounts of each economy without a careful harmonization of growth accounting. Despite the extensive time-series and cross-country coverage, UNIDO does not provide industry-level deflators for output and the stock of capital, which prevents any meaningful study of TFP due to measurement errors. Most importantly, none of them provides information on the stock of ICT vs. non-ICT capital, which is a key variable to test the model's predictions.

Another advantage of KLEMS is that it covers not only manufacturing sectors but also service sectors, which are not included in STAN and UNIDO. However, this comes at some cost: the level of disaggregation of the manufacturing sector in KLEMS is coarser than STAN and UNIDO. Both STAN and UNIDO provide data on output, employment, and capital stock at the ISIC two-digit manufacturing industries, partly explaining their use in the growth literature. To complement our analysis using more disaggregated data on manufacturing sectors, we also present results using STAN productivity data instead of KLEMS. Both labor productivity and TFP are estimated using the industry-level data on the number of employees and the volume of value added and capital stocks. We use STAN ISIC Rev. 3, which covers 23 industries, typically spanning from the early 1990s up to 2009 for most countries in the sample. As a result, the sensitivity test using STAN leaves us with fewer observations than KLEMS.[11]

4.1.1. Measuring uncertainty

Following common practice in the literature (Bloom, 2009; Bachmann et al., 2013; Carrière-Swallow and Céspedes, 2013; Gourio et al., 2013; Caggiano et al., 2014; Choi and Loungani, 2015; Leduc and Liu, 2016), we construct country-specific mea-

[8] For example, Aghion et al. (2010) only use country-level panel data on private investment in structures and housing, but it is questionable whether investment in structures and housing truly proxies productivity-enhancing activity. Aghion et al. (2014) only use industry-level international panel data on productivity growth without testing a composition of investment.

[9] While KLEMS fits better for our own analysis, the two other datasets can be useful for other purposes. For example, STAN includes variables that are not available in KLEMS, such as imports and exports by product group. UNIDO covers both advanced and developing countries and provides more disaggregated manufacturing industries.

[10] See O'Mahony and Timmer (2009) for further details.

[11] The volume of capital stocks is not necessarily observable for a given country/industry/year pair in which the volume of value added and the number of employees are available. This explains why the TFP sample is smaller than the labor productivity sample from the STAN dataset.

sures of time-varying uncertainty using aggregate stock market volatility. This measure of uncertainty is readily available for long periods and allows for straightforward cross-country comparison.[12] Admittedly, this is not a perfect measure of uncertainty as it can reflect abnormal behavior in equity markets rather than capture the aggregate uncertainty faced by firms we consider in our paper. We mitigate this concern by checking the robustness of our results using the economic policy uncertainty indices constructed by Baker et al. (2016), which are less subject to this criticism, and employing an IV approach as in Baker and Bloom (2013).

Specifically, we use realized volatility of aggregate stock market returns from each of the countries in our sample as a proxy for country-specific uncertainty in the baseline regression. Although one would prefer implied volatility over realized volatility, as the former contains forward-looking information, the difference is minor at the annual frequency we consider here. For each country i in our sample and for year t, we calculate annualized realized volatility using daily returns:

$$RV_{i,t} = 100\sqrt{T_i \sum_{s=1}^{T_i} r_{i,s}^2}, \tag{1}$$

where $r_{i,s}$ are daily returns of the stock market i from each trading day s and T_i is the stock market i's number of trading days in a year. We obtain daily closing prices of the major stock exchanges from Global Financial Data, which provides the longest international time-series on stock prices. Table A.1 in the Appendix provides a list of 18 stock exchanges and the sample coverage used to construct uncertainty indices.

Fig. 1 shows the evolution of the 18 country-specific uncertainty indices from 1985 to 2010. Although our measure of uncertainty shows some degree of co-movements across countries, such co-movements are far from perfect. Table 1 further suggests that the average level and the volatility of uncertainty substantially vary across countries. For example, the level of uncertainty in Hungary is twice the level of uncertainty in Australia during our sample period. Both these cross-country and time variations in our uncertainty measure allow identifying the effect of aggregate uncertainty on industry TFP (labor productivity) growth.

4.1.2. Dependence on external finance

Data to construct measures of dependence on external finance are taken from Compustat, which compiles balance sheets and income statements for US-listed firms. Following Rajan and Zingales (1998), dependence on external finance in each industry is measured as the median across all US firms in a given industry of the ratio of total capital expenditures minus current cash flow to total capital expenditures.[13] Fig. 2 shows how industries vary based on their reliance on external finance. Transport Equipment and Food Products, Beverages and Tobacco are among those sectors characterized by a lower dependence on external finance, while Construction and Mining and Quarrying are among those sectors with the highest dependence. The analysis also presents robustness checks using a measure of asset tangibility (Braun and Larrain, 2005).

4.1.3. Some stylized facts

Before proceeding to the empirical analysis, we show some correlations that are present in the raw data using scatter plots. Panel A in Fig. 3 plots the relationship between quarterly aggregate uncertainty and the quarterly aggregate utility-adjusted TFP growth for the US economy during the period 1970–2013. The evidence at the aggregate level is consistent with the existing studies, and Panel B in Fig. 3 suggests that the negative relationship also holds in international data. Interestingly, Fig. 4 shows a positive (negative) relationship between aggregate uncertainty and the sector-level TFP growth for industries with low (high) external finance dependence. We further elaborate on this pattern from the raw data in the following section.

4.2. Empirical methodology

To assess the effect of macroeconomic uncertainty, the analysis follows the methodology proposed by Rajan and Zingales (1998). In particular, the following specification is estimated for an unbalanced panel of 18 advanced economies and 25 industries over the period 1985–2010:

$$TFP_{i,j,t} = \alpha_{i,t} + \gamma_{i,j} + \beta fd_j U_{i,t} + \varepsilon_{i,j,t}, \tag{2}$$

where i denotes countries, j industries, and t years. TFP is TFP growth; fd is a measure of dependence on external finance for each industry j; U is our time-varying measure of uncertainty for each country i; $\alpha_{i,t}$ and $\gamma_{i,j}$ are country-time and country-industry fixed effects, respectively.

The inclusion of these two types of fixed effects provides two important advantages compared to the cross-country analysis: (i) country-year fixed effects allow controlling for any variation that is common to all sectors of a country's economy, including aggregate TFP growth as well as macroeconomic shocks; (ii) country-industry fixed effects allow controlling for

[12] For example, other uncertainty measures such as consumer- or firm-level surveys are not easily comparable across countries owing to the use of different questionnaires. Cross-sectional measures such as the dispersion of firm-level profit, employment, and productivity are not always available for many countries in our sample.

[13] Data have been kindly provided by Hui Tong. For details, see Tong and Wei (2011).

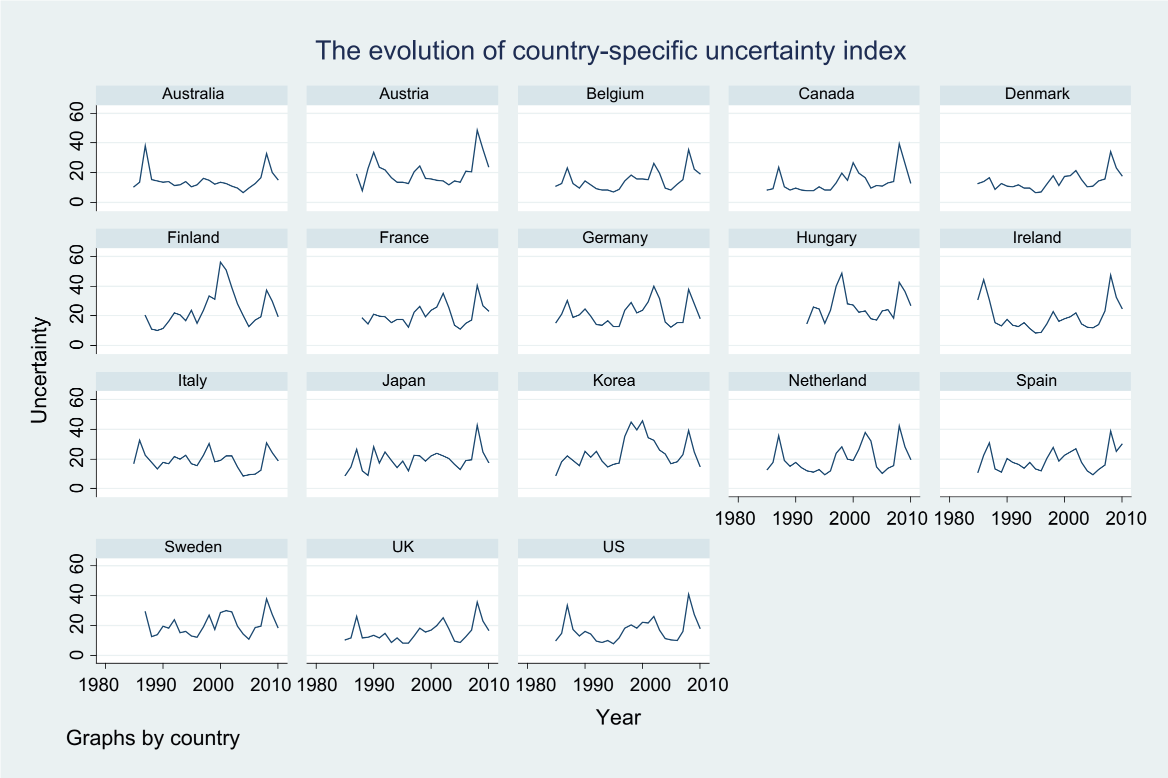

Fig. 1. Evolution of country-specific uncertainty (1985–2010).

Table 1
Descriptive statistics of the country-specific uncertainty indices.

Country	Mean	SD	Obs
Australia	14.66	6.74	26
Austria	19.98	8.94	24
Belgium	14.78	6.63	26
Canada	14.16	7.64	26
Denmark	14.29	5.78	26
Finland	24.33	11.97	24
France	20.89	7.05	23
Germany	21.63	7.75	26
Hungary	26.37	9.39	19
Ireland	19.85	10.10	26
Italy	19.12	6.19	26
Japan	19.56	6.96	26
Korea	24.64	9.88	26
Netherlands	20.06	9.07	26
Spain	19.35	7.31	26
Sweden	20.49	7.07	24
United Kingdom	15.32	6.52	26
United States	17.08	7.99	26

industry-specific factors, including for instance cross-country differences in the TFP growth of certain sectors that could arise from differences in comparative advantages.

As discussed in the previous section, industry dependence on external finance is measured using only US firm-level data. One potential problem with this approach is that US industry dependence on external finance may not be representative of the whole sample—that is, US measures of dependence on external finance may be affected by US-specific regulations or sectoral patterns. However, this issue is unlikely to be important when restricting the analysis to other advanced economies for two main reasons. First, differences in financial dependence are likely to mostly reflect differences in industry-specific factors common across countries, rather than differences across countries' institutional characteristics. For example, if the

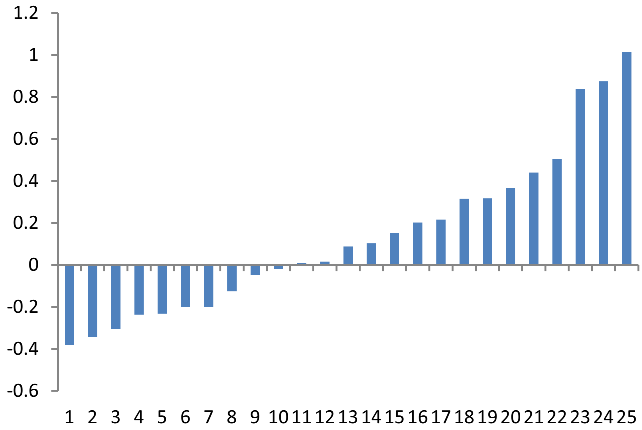

Fig. 2. Dependence on external finance Notes: 1 = Transport Equipment; 2 = Food Products, Beverages and Tobacco; 3 = Chemicals and Chemical Products; 4 = Textiles, Wearing Apparel, Leather and Related Products; 5 = Wood and Paper Products; Printing and Reproduction of Recorded Media; 6 = Education; 7 = Financial and Insurance Activities; 8 = Rubber and Plastics Products, and Mineral Products; 9 = Basic Metals and Fabricated Metal Products, Except Machinery and Equipment; 10 = Electrical and Optical Equipment; 11 = Agriculture, Forestry and Fishing; 12 = Machinery and Equipment N.E.C.; 13 = Electricity, Gas and Water Supply; 14 = Accommodation and Food Service Activities; 15 = Professional, Scientific, Technical, Administrative and Support Service Activities; 16 = Transport and Storage; 17 = Retail Trade, Except Of Motor Vehicles and Motorcycles; 18 = Arts, Entertainment, Recreation and Other Service Activities; 19 = Wholesale and Retail Trade and Repair of Motor Vehicles and Motorcycles; 20 = Wholesale Trade, Except Of Motor Vehicles and Motorcycles; 21 = Health and Social Work; 22 = Real Estate Activities; 23 = Construction; 24 = Mining and Quarrying; 25 = Postal and Courier Activities.

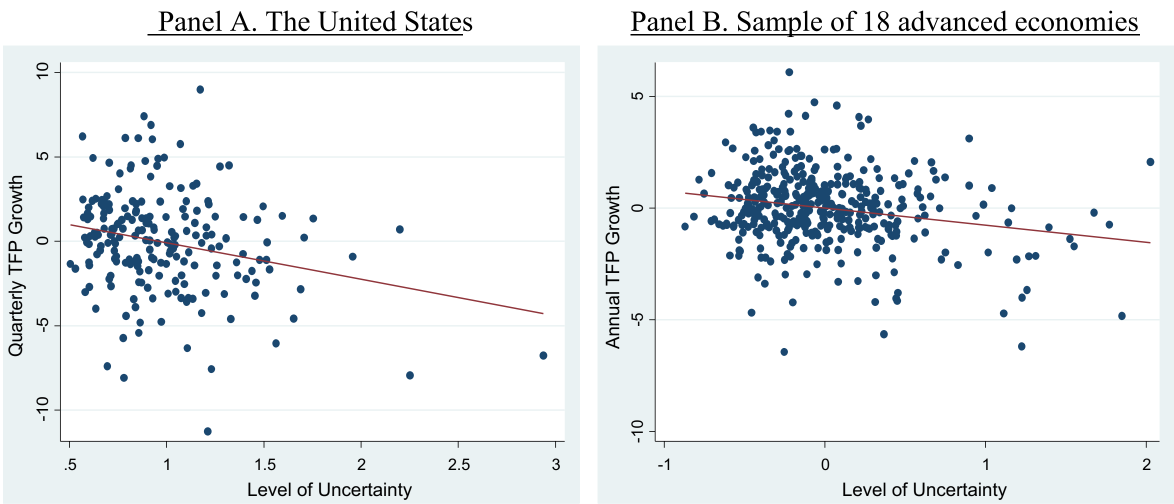

Fig. 3. Uncertainty and TFP growth: correlation at the aggregate level. Coef = −2.16 (−0.76 to 2.8, right); *t*-statistics (based on clustered standard errors) = −3.65 (−3.51 to 2.8, right). Note: this figure shows correlations between quarterly aggregate uncertainty and the quarterly aggregate TFP growth rate for the US from 1970Q1 to 2013Q4 (top) and annual aggregate uncertainty and the annual aggregate TFP growth rate for 18 advanced economies in the sample from 1985 to 2013 (bottom).

electrical machinery sector relies more on external finance than the tobacco sector in the United States, the same pattern is likely to hold also in other advanced economies. Second, given the slow growth convergence process in advanced economies, cross-country differences are likely to persist in our sample.

Eq. (2) is estimated using OLS—and standard errors are clustered at the country-industry level—as the inclusion of country-time and country-industry fixed effects is likely to largely address the endogeneity concerns related to omitted variable bias. In addition, reverse causality issues are unlikely. First, and related to the measure of external dependence, it is hard to conceive that sectoral TFP growth in other countries can influence the degree to which industries rely on external finance in the United States. Second, it is very unlikely that TFP growth at sectoral level can influence aggregate measures of uncertainty. While, in principle, this could be the case if TFP growth co-moves across all sectors, we address this concern when we include country-industry fixed effects. In other words, claiming reverse causality is equivalent to arguing that differences in TFP growth across sectors lead to changes in aggregate uncertainty—which we believe is unlikely.

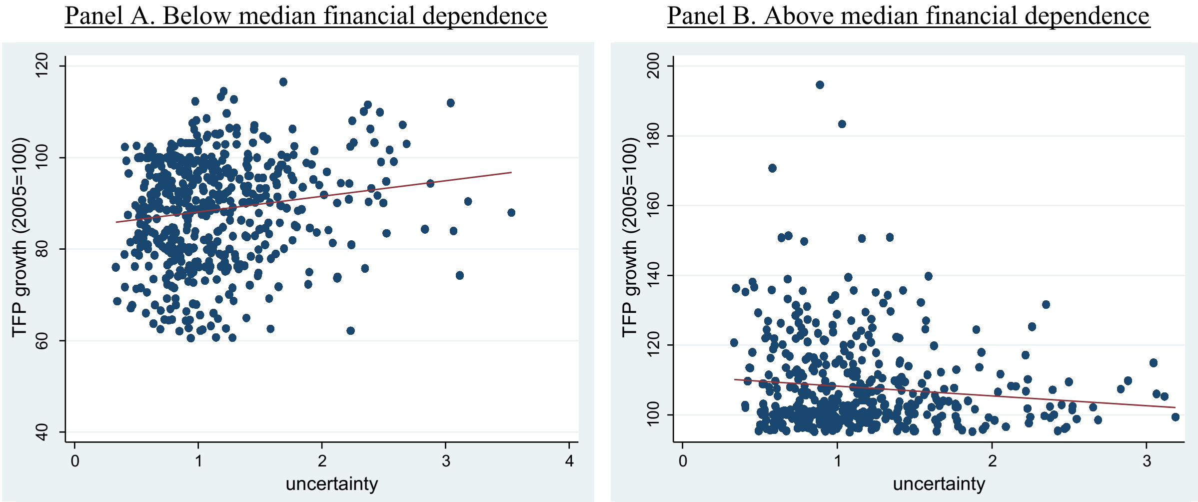

Fig. 4. Uncertainty and TFP growth: correlation at the industry level. Coef = 3.4 (−2.8, right); *t*-statistics (based on clustered standard errors) = 3.6 (−2.9 to 2.8, right). Note: this figure shows how TFP growth changes, on average, over time following an increase in uncertainty in a given country-year for industries that are below (resp. above) median financial dependence.

However, a remaining possible concern in estimating Eq. (2) with OLS is that other macroeconomic variables could affect sector TFP growth when interacted with industries' dependence on external finance. This, in particular, could be the case for the credit-to-GDP ratio—the original variable assessed by Rajan and Zingales (1998), but also for inflation as well as for measures capturing the degree of fiscal counter-cyclicality (Aghion et al., 2014). This issue is addressed in the sub-section on robustness checks. In addition, we also use an IV approach in the same spirit of Baker and Bloom (2013) to mitigate endogeneity concerns.

5. Results

5.1. Baseline results and interpretation

Table 2 presents the results obtained by estimating Eq. (2). It shows that the interaction between uncertainty and external financial dependence is negatively correlated with industry TFP growth. The results corroborate the descriptive evidence presented in Fig. 4. They confirm that the effect of uncertainty on industry TFP growth varies depending on the degree of external financial dependence, and tends to be negative for industries that rely more on external finance.

In particular, the results suggest that the differential TFP growth loss from an increase in uncertainty from the 25th to the 75th percentile of the distribution (approximately one standard deviation) for an industry with relatively low external financial dependence (at the 25th percentile of the distribution) compared to an industry that has relatively high external financial dependence (at the 75th percentile) is about 2.1 percentage points.

5.2. Robustness checks

This section performs several tests to check whether the results presented above are robust to different specifications, subsample analysis, the inclusion of additional variables to address possible omitted variable bias, different dependent variables and datasets, an alternative measure of aggregate uncertainty, and an IV approach.

5.2.1. Different specifications

The results are robust to less restrictive specifications. In particular, similar effects (even though the point estimates are slightly smaller) are obtained when (i) we include only country-time fixed effects and industry dummies but not country-industry fixed effects (Table 2 column II); or (ii) just country, time and industry dummies, but not their interactions (Table 2, column III). Interestingly, since country-time fixed effects are not included, the last specification also suggests that higher uncertainty is associated with lower average industry TFP growth.

In addition, the results are robust when considering the lag of the interaction term between uncertainty and sectoral external finance (Table 2, column IV), as well as when using a categorical measure of external finance—which takes the value one for the sector with the lowest degree of external finance, and 25 for the sector with the largest degree of external finance

Table 2
The effect of uncertainty on TFP growth: baseline.

Explanatory variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)[a]
Uncertainty * financial dependence	−4.102***	−2.889***	−2.513***			−4.296***	−4.125***
	(−3.24)	(−2.98)	(−2.60)			(−3.25)	(−3.13)
Lag of uncertainty * financial dependence				−2.945***			
				(−3.24)			
Uncertainty * financial dependence (ordinal)					−0.214***		
					(−4.25)		
Differential effect in TFP growth (%)	−2.1	−1.5	−1.3	−1.5	−3.3	−2.2	−2.1
Country * time fe	Yes	Yes	No	Yes	Yes	Yes	Yes
Country * sector fe	Yes	No	No	Yes	Yes	Yes	Yes
Controlling for sectoral growth	No	No	No	No	No	Yes	No
Observations	10,654	10,654	10,654	10,654	10,654	10,654	10,329
R^2	0.55	0.27	0.25	0.55	0.55	0.55	0.55

Note: estimates based on Eq. (2). *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively. Differential in TFP computed for an industry whose external financial dependence would increase from the 25th percentile to the 75th percentile of the financial dependence distribution when uncertainty would increase from the 25th to the 75th percentile. The results reported in column (III) are obtained using a specification that separately includes country and time fixed effects —but not their interaction—as well as uncertainty and external finance dependence as controls.
[a] Results obtained by excluding Hungary from the sample.

(Table 2, column V). Finally, the results are also robust when controlling for changes in sectoral growth common to all countries, to account for the possibility that sectoral growth may have co-moved with uncertainty (Table 2, column VI).[14]

5.2.2. Subsample analysis

The theoretical predictions of the effect of uncertainty on TFP growth and the role of credit constraints are likely to be more relevant for manufacturing industries, as these are characterized by a higher share of ICT investment and are typically involved in innovation activities. To check whether this is the case, and to control at the same time for possible measurement errors due to the fact that TFP growth (as well as capital) is typically poorly measured in non-manufacturing sectors, Eq. (2) is estimated separately for manufacturing and non-manufacturing industries.

The results presented in Table 3 shows that the effect of uncertainty on TFP growth varies significantly across sectors. While an increase in uncertainty negatively affects manufacturing industries TFP growth through their dependence on external finance, it does not have a statistically significant effect—at least through this channel—on non-manufacturing industries. Given that the focus of the paper is on advanced economies, we repeated the analysis excluding Hungary from the sample. Not surprisingly, the results remain almost unchanged.

5.2.3. Asset tangibility

We also examine whether the results are robust to replace the RZ index with a measure of asset tangibility—computed as the median fraction of assets represented by net property, plant and equipment for US firms in the same industry for the period 1980–1989 (Braun and Larrain, 2005). The results presented in Table 3 confirm the validity of our results. In particular, we find that the differential TFP growth loss from an increase in uncertainty from 25th to the 75th percentile of the distribution for an industry with relatively high asset tangibility (at the 75th percentile of the distribution) compared to an industry with relatively low asset tangibility (at the 25th percentile of the distribution) is about two percentage points.

5.2.4. Different factors and omitted variable bias

As discussed before, a possible concern in estimating Eq. (2) is that the results are biased due to the omission of macroeconomic variables affecting TFP growth through the dependence on external finance that are at the same time correlated with our measure of uncertainty.

The first obvious candidate is the level of financial development, the variable originally used by Rajan and Zingales (1998) in their approach. To check whether the inclusion of this variable alters the effect of uncertainty on industry TFP growth, we augment Eq. (2) by interacting the ratio of bank credit to GDP (the main variable used in Rajan and Zingales, 1998) with the degree of dependence on external finance. The results presented in the first column of Table 4 show that the effect of uncertainty on industry TFP growth remains of the same sign and also statistically significant, even though the point estimates are smaller. In particular, the results suggest that the differential TFP growth loss from an increase in uncertainty from the 25th to the 75th percentile of the distribution for an industry with relatively low external financial dependence compared to an industry that has relatively high external financial dependence is about 2 percentage points.[15]

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[14] We thank an anonymous referee for suggesting this robustness check.

[15] In contrast, the interaction of financial development and financial dependence is negatively correlated with industry TFP growth (for similar results, see also Aghion et al., 2014). However, consistent with Rajan and Zingales (1998), we find that an increase in financial development raises industry valued added growth the more so for industries with higher financial dependence, suggesting that the main channel through which the effect materializes is an increase in inputs of production, notably investment (see, for example, Chapter 3 of the IMF WEO April 2015).

Table 3
The effect of uncertainty on TFP growth: manufacturing versus non-manufacturing.

Explanatory variable	(I)	(II)	(III)
	Manufacturing		Non-Manufacturing
Uncertainty * financial dependence	−4.423***		−1.107
	(−3.23)		(−0.43)
Uncertainty * asset tangibility		−18.203***	
		(−3.24)	
Differential effect in TFP growth (%)	−2.3	−2.0	−0.6
Observations	6612	6612	4042
R^2	0.57	0.64	0.58

Note: estimates based on Eq. (2). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively. The differential in TFP is computed for an industry whose external financial dependence would increase from the 25th percentile to the 75th percentile of the financial dependence distribution, with uncertainty increasing from the 25th to the 75th percentile. The differential in TFP is computed for an industry whose asset tangibility would decrease from the 75th percentile to the 25th percentile of the asset tangibility distribution, with uncertainty increasing from the 25th to the 75th percentile.

Table 4
The effect of uncertainty on TFP growth: controlling for other effects.

Explanatory variable	(I)	(II)	(III)	(IV)	(V)
Uncertainty * financial dependence	−2.921**	−4.104***	−2.824***	−2.980***	−2.276**
	(−2.55)	(−3.27)	(−2.62)	(−2.44)	(−2.03)
Credit to GDP * financial dependence	−0.149***				−0.134**
	(−2.75)				(−2.51)
Inflation * financial dependence		0.224			0.395
		(0.47)			(0.84)
Government size * financial dependence			0.512*		0.133
			(1.64)		(0.23)
Budget balance * financial dependence				−0.665***	−0.254
				(−2.52)	(−0.48)
Differential effect in TFP growth (%)	−1.5	−2.1	−1.5	−1.5	−1.2
Observations	10,505	10,654	9559	9459	9310
R^2	0.55	0.55	0.53	0.53	0.54

Note: estimates based on Eq. (2). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively. The differential in TFP is computed for an industry whose external financial dependence would increase from the 25th percentile to the 75th percentile of the financial dependence distribution, with uncertainty increasing from the 25th to the 75th percentile.

Another potential variable that may affect industry TFP growth through external financial dependence is inflation. Inflation may lead to capital misallocation and to the extent that more financially dependent sectors are those that suffer more from capital misallocation, it may have larger negative effects on industries that rely more on external sources of financing. Moreover, inflation may affect industry TFP growth by increasing price level uncertainty. To further check the robustness of our results, we include an interaction term between inflation and external financial dependence as a control. The results reported in the second column of Table 4 show that the effect of uncertainty on industry TFP growth is unchanged, while inflation does not statistically significantly affect industry TFP growth.

An additional variable that may affect TFP growth through external financial dependence is the degree of fiscal counter-cyclicality. In particular, Aghion et al. (2014) show that an increase in a country's degree of fiscal counter-cyclicality raises productivity growth the more so for industries with higher financial dependence. Since measures of fiscal counter-cyclicality are typically time-unvarying we use two alternative proxies: (i) the size of the government—which is typically found to be one of the main determinants of the degree of fiscal counter-cyclicality (Fatás and Mihov, 2001)—proxied by the ratio of government consumption to GDP; and (ii) the budget balance-to-GDP ratio. The results obtained controlling for these variables interacted with dependence on external finance show that the effect of uncertainty on industry TFP growth remains statistically significant. Moreover, we find that the interaction between government size (budget balance) and external finance is positively (negatively) correlated with industry TFP growth (Table 4, columns III and IV), which is consistent with Aghion et al. (2014). Finally, the results are also robust when these four controls are included simultaneously (Table 4, column V).

5.2.5. Different dependent variable

A possible concern regarding the results is that they might be driven by measurement errors, as TFP growth is not observable. To overcome possible measurement errors, we repeat the estimation using labor productivity growth as a dependent variable. Moreover, by comparing the effect on TFP and productivity growth, we can infer whether uncertainty has any effect on capital deepening.[16]

[16] Productivity growth is the sum of TFP growth and (weighted) capital deepening. Given the OLS properties, it is possible to decompose the effect of uncertainty on productivity growth as the sum of its effects on TFP growth and capital deepening.

The results presented in Table 5 show that the interaction between uncertainty and external financial dependence is negatively correlated with labor productivity TFP growth. In particular, the baseline results reported in the first column of the table suggest that the differential labor productivity growth loss from an increase in uncertainty from the 25th to the 75th percentile of the distribution for an industry with relatively low external financial dependence compared to an industry that has relatively high external financial dependence is about 2.2 percentage points. Interestingly, the magnitude of the effect is only slightly larger than the one on TFP growth, suggesting that uncertainty has little effects on industry capital deepening through external finance.

5.2.6. Alternative uncertainty measure

As an additional robustness check, we re-estimate Eq. (2) using the economic policy uncertainty index constructed by Baker et al. (2016). Unlike stock market volatility, the economic policy uncertainty index is based on the newspaper coverage frequency of policy-related economic uncertainty. Baker et al. (2016) conduct comprehensive searches of newspapers for relevant terms, such as "uncertain" or "uncertainty"; "economic", "economy" or "commerce"; and policy-relevant terms, such as "central bank", "deficit", "trade policy", or "ministry of finance". For countries other than Canada, the UK, and the US, they conduct searches in the native language of the newspaper for relevant terms. In the recent literature, the economic policy uncertainty index has been widely used to complement the measure of uncertainty based on financial market data (Bachmann et al., 2013; Caggiano et al., 2014; Choi and Loungani, 2015; Bernal et al., 2016; Gulen and Ion, 2016).

The main advantage of this measure is that it does not rely on financial market data, which are also driven by risk appetite of international investors rather than uncertainty *per se*, and is, therefore, less subject to reverse causality. Its main shortcoming is that it is available for only 10 countries (Canada, France, Germany, Italy, Japan, Korea, the Netherlands, Spain, the U.K., and the U.S.) in our sample, and for most only since the mid-90 s.[17]

Nevertheless, the results presented in Table 6 show that the statistical significance of the results is robust to the use of this alternative measure, and the magnitude of the effect is even larger.[18] In particular, the differential TFP (labor productivity growth) loss from an increase in economic policy uncertainty from the 25th to the 75th percentile of the distribution for an industry with relatively low external financial dependence compared to an industry that has relatively high external financial dependence is about 4 (4.6) percentage points.

5.2.7. Alternative dataset

As discussed in the previous section, a main shortcoming of the KLEMS database is that the level of disaggregation may be too coarse for manufacturing industries. To complement our analysis using more disaggregated data, we replace KLEMS productivity data with STAN. Both labor productivity and TFP are estimated using the industry-level data on the number of employees and the volume of value added and capital stocks.

The results of this exercise presented in Table 7 confirm that uncertainty (economic policy uncertainty) tends to reduce TFP (productivity) growth in those industries that rely more on external finance. In addition, the magnitude of the results is similar and not statistically different from that found using the KLEMS database.

5.2.8. IV approach

We also address endogeneity concerns using an IV approach in the same spirit of Baker and Bloom (2013). Specifically, we use the following set of exogenous disasters as instruments: (i) natural disasters—extreme weather and geological events as defined by the Center for Research on the Epidemiology of Disasters (CRED); (ii) terrorist attacks: high casualty terrorist bombing as defined by the Center for Systemic Peace (CPS).[19]

We proceed in a two-step. In the first step, we regress uncertainty on these indicators, controlling for time- and country-fixed effects. The results of the first stage confirm that these two instruments can be considered as "strong instruments"—that is, the joint F-test is above the canonical value (10) identified by Staiger and Stock (1997). In the second step, we re-estimate Eq. (2) using the exogenous part of uncertainty driven by these two instruments—that is, the fitted value of the first step.[20] The results reported in Table 8 confirm that an increase in uncertainty reduces TFP (productivity) growth for industries that rely more on external finance. In addition, the magnitude of the effect is similar and not statistically different from the one obtained using OLS, confirming that endogeneity is not a great concern.

[17] By construction, the economic policy uncertainty index is less prone to contagion in international financial markets, resulting in much lower cross-country correlations than stock market volatility.

[18] The larger effect is only partly driven by the different sample composition. Indeed, repeating the baseline regression for the sample for which the measure of economic policy uncertainty is available produces a TFP differential effect of about 2.6 percentage points.

[19] See Baker and Bloom (2013) for details on the constructions of these instruments and on the tests regarding the exogeneity of these measures. We do not use political shocks as in our sample none of these events has occurred.

[20] In the second step, we bootstrap the standard errors to account for the fact that our left-hand side variable is estimated.

Table 5
The effect of uncertainty on productivity growth: controlling for other effects.

Explanatory variable	(I)	(II)	(III)	(IV)	(V)	(VI)
Uncertainty * financial dependence	−4.251***	−2.946***	−4.220***	−2.915***	−3.083***	−2.400**
	(−3.59)	(−2.81)	(−3.58)	(−2.74)	(−2.82)	(−2.15)
Credit to GDP * financial dependence		−0.184***				−0.153***
		(−3.13)				(−2.84)
Inflation * financial dependence			0.515			0.513
			(1.03)			(0.89)
Government size * financial dependence				0.425		−0.004
				(1.40)		(−0.01)
Budget balance * financial dependence					−0.613***	−0.287
					(−2.22)	(−0.59)
Differential effect in productivity growth (%)	−2.2	−1.5	−2.2	−1.5	−1.6	−1.2
Observations	11,083	10,929	10,654	9899	9799	9310
R^2	0.61	0.62	0.61	0.62	0.62	0.54

Note: estimates based on Eq. (2). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively. The differential in productivity in computed for an industry whose external financial dependence would increase from the 25th percentile to the 75th percentile of the financial dependence distribution, with uncertainty increasing from the 25th to the 75th percentile.

Table 6
The effect of economic policy uncertainty on TFP and labor productivity growth.

Explanatory variable	(I) TFP growth	(II) Productivity growth
Economic policy uncertainty * financial dependence	−0.081*	−0.093**
	(−1.62)	(−2.03)
Differential effect	−4.0	−4.6
Observations	4552	4042
R^2	0.51	0.60

Note: estimates based on Eq. (2). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively. The differential effect is computed for an industry whose external financial dependence would increase from the 25th percentile to the 75th percentile of the financial dependence distribution, with uncertainty increasing from the 25th to the 75th percentile.

Table 7
The effect of uncertainty on TFP and labor productivity growth: STAN database.

Explanatory variable	(I) TFP growth	(II) Productivity growth	(III) TFP growth	(IV) Productivity growth
Uncertainty * financial dependence	−0.247***	−0.171***		
	(−3.33)	(−5.52)		
Economic policy uncertainty * financial dependence			−0.066***	−0.042*
			(−3.08)	(−1.87)
Differential effect	−2.0	−1.4	−2.7	−1.7
Observations	2701	5822	1058	2349
R^2	0.28	0.21	0.30	0.30

Note: estimates based on Eq. (2). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively. The differential effect is computed for an industry whose external financial dependence would increase from the 25th percentile to the 75th percentile of the financial dependence distribution, with uncertainty increasing from the 25th to the 75th percentile.

5.3. Nonlinearities

5.3.1. Degree of uncertainty

The previous section has provided strong and robust evidence of the effect of uncertainty on industry TFP growth. An interesting question is whether the effect is nonlinear and materializes only above a certain uncertainty threshold. Using a logistic smooth transition autoregressive model, Jones and Enders (2016) find that the effects of uncertainty shocks on macroeconomic activity are nonlinear at the aggregate level. To address this question, we perform two empirical exercises. The first consists of augmenting Eq. (2) with an interaction term between the square of uncertainty and external financial dependence:

Table 8
The effect of economic policy uncertainty on TFP and labor productivity growth: IV approach.

Explanatory variable	(I) TFP growth	(II) Productivity growth	
Uncertainty * financial dependence	−5.349***	−3.530**	
	(−4.21)	(−3.12)	
Differential effect	−2.8	−1.8	
Observations	10,505	11,083	
R^2	0.56	0.65	
IV-first stage			
Natural disasters (lagged)			0.065***
			(5.84)
Terroristic attacks (lagged)			0.089***
			(4.20)
F-test			21.04
Country fe			Yes

Note: estimates based on Eq. (2). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively. The differential effect is computed for an industry whose external financial dependence would increase from the 25th percentile to the 75th percentile of the financial dependence distribution, with uncertainty increasing from the 25th to the 75th percentile.

$$TFP_{j,i,t} = \alpha_{i,t} + \gamma_{i,j} + \beta fd_j U_{i,t} + \delta fd_j U_{i,t}^2 + \varepsilon_{i,j,t}. \tag{3}$$

In the second exercise, we allow the effect of uncertainty to be different in countries-periods where the measure of uncertainty is below (above) its historical median:

$$TFP_{j,i,t} = \alpha_{i,t} + \gamma_{i,j} + \beta^{U+} fd_j D_{i,t} U_{i,t} + \beta^{U-} fd_j (1 - D_{i,t}) U_{i,t} + \varepsilon_{i,j,t}, \tag{4}$$

where *D* is a dummy variable which takes the value one when in a given country in a given time uncertainty is above its historical median, and zeros otherwise.

The results obtained by estimating Eqs. (3) and (4) are reported in Table 9. They suggest that the effect of uncertainty on industry TFP (labor productivity) growth does not significantly depend on the level of uncertainty itself.

5.3.2. Degree of external finance

Another interesting question is whether the effect of uncertainty—through external finance—on TFP (productivity) growth is larger in industries that are more financially constrained. To test this hypothesis, the following equation is estimated:

$$TFP_{j,i,t} = \alpha_{i,t} + \gamma_{i,j} + \beta fd_j U_{i,t} + \delta D_j U_{i,t} + \varepsilon_{i,j,t}, \tag{5}$$

where *D* is a dummy variable which takes value one for industries that rely relatively more heavily on external finance—that is, with a degree of external finance above the 75th percentile of distribution—and zero otherwise.[21]

The results presented in Table 10 suggest that the effect of uncertainty is negative but not statistically significant across all industries. In contrast, it is larger and statistically significant in industries that are more financially constrained.[22] This result is consistent with the evidence presented in Ghosal and Loungani (2000) on the greater effect of uncertainty for small firms which are typically more financially constrained.

5.4. Recessions vs. expansions

The theoretical argument that uncertainty negatively affects TFP growth in industries that rely more on external finance builds on the assumption that credit constraints are more binding in low growth regimes (recessions). Moreover, using smooth transition VARs, Caggiano et al. (2014) and Popp and Zhang (2016) find that the negative effects of uncertainty shocks on US output, employment, and investment are more pronounced during recessions than expansions. Two approaches are used to assess whether the effect of uncertainty on industry TFP growth via financial constraints is more negative in bad times. In the first approach, we adopt the smooth transition approach proposed by Auerbach and Gorodnichenko (2012) and estimate the following regression:

[21] Qualitatively similar results are obtained when considering different thresholds, such as the median or the 66th percentile of the distribution of external finance. See also Table A.3 in the Appendix.
[22] The overall effect of uncertainty on relatively more financially constrained industries is given by $\beta + \delta$. The F-test suggests that this effect is statistically significant at one percent.

Table 9
The effect of uncertainty on TFP and productivity growth: testing for nonlinearities (uncertainty).

Explanatory variable	(I)	(II)	(III)	(IV)
	TFP growth		Productivity growth	
Uncertainty * financial dependence	−4.629		−5.097	
	(−1.27)		(−1.55)	
Uncertainty^2 * financial dependence	0.167		0.268	
	(0.14)		(0.25)	
Low uncertainty * financial dependence		−8.685***		−7.735***
		(−2.71)		(−2.64)
High uncertainty * financial dependence		−5.502***		−5.315***
		(−3.17)		(−3.34)
Observations	10,564	10,564	10,654	9899
R^2	0.55	0.55	0.61	0.61

Note: estimates based on Eqs. (3) and (4). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively.

Table 10
The effect of uncertainty on TFP and productivity growth: testing for nonlinearities (financial dependence).

Explanatory variable	(I) TFP growth	(II) Productivity growth
Uncertainty * financial dependence	−1.548	−0.295
	(−0.79)	(−0.18)
Uncertainty * high financial dependence	−2.441*	−3.785***
	(−1.80)	(−2.62)
Observations	10,564	10,654
R^2	0.55	0.61

Note: estimates based on Eq. (5). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively.

$$TFP_{j,i,t} = \alpha_{i,t} + \gamma_{i,j} + \beta^L fd_j F(z_{i,t}) U_{i,t} + \beta^H fd_j (1 - F(z_{i,t})) U_{i,t} + \varepsilon_{i,j,t} \tag{6}$$

$$\text{with } F(z_{it}) = \frac{\exp(-\theta z_{it})}{1 + \exp(-\theta z_{it})}, \quad \theta > 0,$$

where z is an indicator of the state of the economy normalized to have zero mean and unit variance, and $F(z_{it})$ is the corresponding smooth transition function between the states. Our analysis uses contemporaneous GDP growth as a measure of the state of the economy.[23] The results presented in Table 11 (columns I and II) suggest that the effects of uncertainty on industry TFP (labor productivity) growth are very different across economic regimes.[24] During the periods of low growth, an increase in uncertainty reduces TFP (labor productivity) growth in those industries that heavily rely on external finance, but during periods of high growth, the effect is not statistically different from zero.

In the second approach, we modify Eq. (6) by replacing $F(z_{it})$ with a dummy that takes value one when output gaps are below the historical sample median (−0.3), and zero otherwise.[25] The results obtained by estimating this specification suggest that the effect of uncertainty on TFP (productivity) growth is larger during the periods of negative output gaps than positive ones (Table 11, columns III and IV). Overall, these findings are consistent with the theoretical predictions of a larger negative effect of uncertainty when the economy is in a downturn, and credit constraints are more binding.

5.5. Mechanisms: The role of ICT capital

As discussed in Section 3, a mechanism through which uncertainty can negatively affect TFP (productivity) growth is by leading credit constrained firms to switch the composition of investment away from productive-enhancing investment, which is more subject to liquidity risk (Aghion et al., 2010).

We test this mechanism by considering as a dependent variable in Eq. (2) the share of ICT capital in the total capital stock. The results reported in Table 12 (column I) show that uncertainty reduces the ICT capital share in firms that are more credit

[23] Following Auerbach and Gorodnichenko (2012), we use $\theta = 1.5$ for the analysis of recessions and expansions.
[24] Similar results are also obtained when the sample period is restricted to 2007, suggesting that they are not driven mainly by the Great Recession.
[25] Estimates of output gaps are taken from the OECD Economic Outlook Database (2015).

Table 11
The effect of uncertainty on TFP and productivity growth: the role of business cycle.

Explanatory variable	(I) TFP growth	(II) Productivity growth	(III) TFP growth	(IV) Productivity growth
Uncertainty * financial dependence * recessions	−8.002**	−8.960***		
	(−2.24)	(−3.41)		
Uncertainty * financial dependence * expansions	−0.483	−0.132		
	(−0.21)	(−0.07)		
Uncertainty * financial dependence * negative output gaps			−4.859***	−5.636***
			(−2.51)	(−3.91)
Uncertainty * financial dependence * positive output gaps			−3.829**	−3.324**
			(−2.51)	(−2.55)
Observations	10,529	10,654	10,529	10,654
R^2	0.55	0.61	0.55	0.61

Note: estimates based on Eq. (6). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively.

Table 12
The effect of uncertainty on the share of ICT capital in the total capital stock.

Explanatory variable	(I) Baseline	(II) Controlling for other factors	(III) Economic Policy Uncertainty	(IV) IV	(V) Recessions vs. Expansions
Uncertainty * financial dependence	−1.514**	−1.259**	−0.034**	−2.836***	
	(−2.18)	(−1.96)	(−2.55)	(−3.38)	
Uncertainty * financial dependence * recessions					−2.854***
					(−3.83)
Uncertainty * financial dependence * expansions					0.596 (0.66)
Differential effect in share of ICT capital (percentage points)	−0.8	−0.6	−1.7	−1.5	
Observations	8899	8178	3908	8899	8797
R^2	0.80	0.81	0.89	0.80	0.80

Note: estimates based on Eqs. (2) and (6). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively. The differential in the share of ICT capital in the total capital stock is computed for an industry whose external financial dependence would increase from the 25th percentile to the 75th percentile of the financial dependence distribution, with uncertainty increasing from the 25th to the 75th percentile. Results in columns two obtained by controlling for the interaction between financial dependence and the credit-to-GDP ratio (inflation, government size and budget balance).

constrained. In particular, the differential decline in the share of ICT capital from an increase in uncertainty from the 25th to the 75th percentile of the distribution for an industry with relatively low external financial dependence compared to an industry that has relatively high external financial dependence is about 0.8 percentage point.[26] Moreover, the results reported in Table A.2 show that uncertainty has statistically significant negative effects on the level of ICT capital but not on non-ICT capital.

These results are robust to the various checks presented before, including: (i) controlling for the interaction of several macroeconomic variables and the degree of external financial dependence (Table 12, column II); (ii) using economic policy uncertainty (column III); (iii) estimating the effect using the IV approach (column IV).

In addition, consistent with the fact that credit constraints are more binding in periods of relatively weak growth, we find that the effect is larger during recessions than during expansions. In particular, the results presented in Table 12 (column V) suggest that the effects of uncertainty on the share of ICT capital are very different across economic regimes.[27] During the periods of low growth, an increase in uncertainty reduces the ICT capital share in those industries that heavily rely on external finance, but during periods of high growth, the effect is not statistically different from zero.

6. Conclusion

Using an extensive international dataset and the Rajan and Zingales (1998) methodology, we present evidence on how credit constraints (measured by the dependence on external finance) interact with an increase in uncertainty in determining industry-level productivity growth. We find that an increase in aggregate uncertainty reduces the share of more productive capital and productivity growth more in industries that heavily depend on external finance and there is strong asymmetry in the interaction effect between recessions and expansions.

[26] The magnitude of the results is consistent with the effect on TFP growth. In particular, the results obtained by estimating Eq. (2) using the share of ICT capital in the total stock of capital suggest that 1.5 percentage points increase in the share of ICT capital (approximately 20 percent in our sample) is associated with an increase in TFP growth of about 5 percentage points.

[27] Similar results are also obtained when the sample period is restricted to 2007, suggesting that they are not driven mainly by the Great Recession.

Regarding heightened uncertainty and worldwide productivity slowdown since the global financial crisis, our paper offers timely insights on the link between uncertainty and growth. In particular, the role of financial constraints we found in the paper suggests a beneficiary role of counter-cyclical policies on productivity growth during uncertain times—which corroborates conclusions of Aghion et al. (2014, 2015) that financially constrained sectors grow faster in countries with more counter-cyclical fiscal and monetary policies—as well as of policies aimed at addressing weak corporate balance sheets.

Appendix A

See Tables A.1–A.3.

Table A.1
Description of stock market data used to construct uncertainty indices.

Country	Stock exchanges	Coverage
Australia	Australia ASX All-Ordinaries (w/GFD extension)	1985–2010
Austria	Austria Trading Index (ATX)	1987–2010
Belgium	Brussels All-Share Price Index (w/GFD extension)	1985–2010
Canada	Canada S&P/TSX 300 Composite (w/GFD extension)	1985–2010
Denmark	OMX Copenhagen All-Share Price Index	1985–2010
Finland	OMX Helsinki All-Share Price Index	1987–2010
France	Paris CAC-40 Index	1988–2010
Germany	Germany DAX Price Index	1985–2010
Hungary	Budapest Stock Exchange Index (BUX)	1992–2010
Ireland	Ireland ISEQ Overall Price Index (w/GFD extension)	1985–2010
Italy	Banca Commerciale Italiana Index (w/GFD extension)	1985–2010
Japan	Tokyo SE Price Index (TOPIX) (w/GFD extension)	1985–2010
Korea	Korea SE Stock Price Index (KOSPI)	1985–2010
Netherland	Amsterdam AEX Stock Index	1985–2010
Spain	Madrid SE General Index (w/GFD extension)	1985–2010
Sweden	OMX Stockholm All-Share Price Index	1987–2010
United Kingdom	UK FTSE All-Share Index (w/GFD extension)	1985–2010
United States	S&P 500 Composite Price Index (w/GFD extension)	1985–2010

Table A.2
The effect of uncertainty on ICT and non-ICT capital (percent).

Explanatory variable	(I) ICT capital	(II) Non-ICT capital
Uncertainty * financial dependence	−1.116**	−0.022
	(−2.25)	(−0.07)
Observations	8819	8819
R^2	0.47	0.56

Note: estimates based on Eq. (2). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively. Differential in TFP computed for an industry whose external financial dependence would increase from the 25th percentile to the 75th percentile of the financial dependence distribution when uncertainty would increase from the 25th to the 75th percentile.

Table A.3
The effect of uncertainty on TFP and productivity growth: testing for nonlinearities (financial dependence).

Explanatory variable	(I) TFP growth	(II) Productivity growth
Uncertainty * low financial dependence	0.980	0.759
	(1.18)	(0.98)
Uncertainty * high financial dependence	−3.495***	−3.702***
	(−2.97)	(−2.70)
Observations	10,564	10,654
R^2	0.55	0.61

Note: estimates based on Eq. (5). Country * time and country * sector fixed effects included. *T*-statistics based on clustered standard errors at the country-industry level are reported in parenthesis. *, **, *** denote significance at 10, 5 and 1 percent, respectively.

References

Acemoglu, Daron, Johnson, Simon, Robinson, James, Thaicharoen, Yunyong, 2003. Institutional causes, macroeconomic symptoms: volatility, crises and growth. J. Monetary Econ. 50, 49–123.
Aghion, Philippe, Angeletos, George-Marios, Banerjee, Abhijit, Manova, Kalina, 2010. Volatility and growth: credit constraints and the composition of investment. J. Monetary Econ. 57 (3), 246–265.
Aghion, Philippe, Farhi, Emmanuel, Kharroubi, Enisse, 2015. Liquidity and growth: the role of counter-cyclical interest rates. Mimeo.
Aghion, Philippe, Hemous, David, Kharroubi, Enisse, 2014. Cyclical fiscal policy, credit constraints, and industry growth. J. Monetary Econ. 62, 41–58.
Arellano, Cristina, Bai, Yan, Kehoe, Patrick, 2010. Financial markets and fluctuations in uncertainty. Federal Reserve Bank of Minneapolis Working Paper.
Auerbach, Alan J., Gorodnichenko, Yuriy, 2012. Measuring the output responses to fiscal policy. Am. Econ. J.: Econ. Policy, 1–27.
Bachmann, Rüdiger, Bayer, Christian, 2013. Wait-and-see business cycles? J. Monetary Econ. 60 (6), 704–719.
Bachmann, Rüdiger, Elstner, Steffen, Sims, Eric R., 2013. Uncertainty and economic activity: evidence from business survey data. Am. Econ. J.: Macroeconomics 5 (2), 217–249.
Baker, Scott R., Bloom, Nicholas, 2013. Does uncertainty reduce growth? Using disasters as natural experiments. No. w19475. National Bureau of Economic Research.
Baker, Scott R., Bloom, Nicholas., Davis, Steven J., 2016. Measuring economic policy uncertainty. Quart. J. Econ. 131 (4), 1593–1636.
Bernal, Oscar, Gnabo, Jean-Yves, Guilmin, Grégory, 2016. Economic policy uncertainty and risk spillovers in the Eurozone. J. Int. Money Finance 65, 24–45.
Bernanke, Ben, 1983. Irreversibility, uncertainty, and cyclical investment. Quart. J. Econ. 97(1) (1983) 85–106.
Bloom, Nicholas, 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–685.
Bloom, Nicholas, 2014. Fluctuations in uncertainty. J. Econ. Persp., 153–175
Bloom, Nicholas, Floetotto, Max, Jaimovich, Nir, Eksten, Itay Saporta, Terry, Stephen, 2014. Really uncertain business cycles. US Census Bureau Center for Economic Studies Paper No. CES-WP-14-18.
Braun, Matias, Larrain, Borja, 2005. Finance and the business cycle: international, inter-industry evidence. J. Finance 60 (3), 1097–1128.
Bulan, Laarni T., 2005. Real options, irreversible investment and firm uncertainty: new evidence from US firms. Rev. Financial Econ. 14 (3), 255–279.
Byun, Sungje, Jo, Soojin, 2018. Heterogeneity in the dynamic effects of uncertainty on investment. Can. J. Econ. (forthcoming).
Caggiano, Giovanni, Castelnuovo, Efrem, Groshenny, Nicolas, 2014. Uncertainty shocks and unemployment dynamics in US recessions. J. Monetary Econ. 67, 78–92.
Caldara, Dario, Cristina, Fuentes-Albero, Simon, Gilchrist, Egon, Zakrajšek, 2016. The macroeconomic impact of financial and uncertainty shocks. Eur. Econ. Rev. 88, 185–207.
Cappellari, Lorenzo, Dell'Aringa, Carlo, Leonardi, Marco, 2012. Temporary employment, job flows and productivity: a tale of two reforms. Econ. J. 122 (562), F188–F215.
Carrière-Swallow, Yan., Céspedes, Luis Felipe, 2013. The impact of uncertainty shocks in emerging economies. J. Int. Econ. 90 (2), 316–325.
Choi, Sangyup, 2016. The impact of US financial uncertainty shocks on emerging market economies: an international credit channel. Working paper.
Choi, Sangyup, Loungani, Prakash, 2015. Uncertainty and unemployment: the effects of aggregate and sectoral channels. J. Macroecon. 46, 344–358.
Christiano, Lawrence J., Motto, Roberto, Rostagno, Massimo, 2014. Risk shocks. Am. Econ. Rev. 104 (1), 27–65.
Dolado, Juan J., Ortiguira, Salvador, Stucchi, Rodolfo, 2012. Does dual employment protection affect TFP? Evidence from Spanish manufacturing firms. CEPR Discussion Papers no. 8763.
Durnev, Art, 2012. The real effects of political uncertainty: elections and investment sensitivity to stock prices. Mimeo.
Fatás, A., Mihov, I., 2001. Government size and automatic stabilizers: international and intranational evidence. J. Int. Econ. 55 (1), 3–28.
Foote, David A., Folta, Timothy, 2002. Temporary workers as real options. Human Resour. Manage. Rev. 12 (4), 579–597.
Ghosal, Vivek, Loungani, Prakash, 2000. The differential impact of uncertainty on investment in small and large businesses. Rev. Econ. Stat. 82 (2), 338–343.
Ghosal, Vivek, Loungani, Prakash, 1996. Product market competition and the impact of price uncertainty on investment: some evidence from US manufacturing industries. J. Indust. Econ. 44 (2), 217–228.
Gilchrist, Simon, Sim, Jae W., Zakrajšek, Egon, 2014. Uncertainty, financial frictions, and investment dynamics. No. w20038. National Bureau of Economic Research.
Gourio, Francois, Siemer, Michael, Verdelhan, Adrien, 2013. International risk cycles. J. Int. Econ. 89 (2), 471–484.
Gulen, Huseyin, Ion, Mihai, 2016. Policy uncertainty and corporate investment. Rev. Financial Stud. 29 (3), 523–564.
Handley, Kyle, Limao, Nuno, 2015. Trade and investment under policy uncertainty: theory and firm evidence. Am. Econ. J.: Econ. Policy 7 (4), 189–222.
Imbs, Jean, 2007. Growth and volatility. J. Monetary Econ. 54 (7), 1848–1862.
IMF World Economic Outlook, April 2015, Chapter 3. "Where are we headed? Perspectives on potential output". International Monetary Fund, 2015.
Jones, Paul M., Enders, Walter, 2016. The asymmetric effects of uncertainty shocks on macroeconomic activity. Macroeconomic Dyn. 1–28.
Julio, Brandon, Yook, Youngsuk, 2012. Political uncertainty and corporate investment cycles. J. Finance 67 (1), 45–83.
King, Robert G., Levine, Ross, 1993. Finance and growth: Schumpeter might be right. Quart. J. Econ., 717–737
Kleinknecht, Alfred, Oostendorp, Remco M., Pradhan, Menno P., Naastepad, C.W.M., 2006. Flexible labour, firm performance and the Dutch job creation miracle. Int. Rev. Appl. Econ. 20 (02), 171–187.
Leahy, John, Whited, Toni M., 1996. The effects of uncertainty on investment: some stylized facts. J. Money, Credit, Banking 28 (1), 64–83.
Leduc, Sylvain, Liu, Zheng, 2016. Uncertainty shocks are aggregate demand shocks. J. Monetary Econ. 82 (September), 20–35.
Lotti, Francesca, Viviano, Eliana, 2012. Temporary Workers, Uncertainty and Productivity. The Society of Labor Economists (Mimeo).
Martin, Philippe, Rogers, Carol Ann, 2000. Long-term growth and short-term economic instability. Eur. Econ. Rev. 44 (2), 359–381.
Michie, Jonathan, Sheehan, Maura, 2003. Labour market deregulation, flexibility and innovation. Can. J. Econ. 27 (1), 123–143.
O'Mahony, Mary, Timmer, Marcel P., 2009. Output, input and productivity measures at the industry level: the EU KLEMS database. Econ. J. 119 (538), F374–F403.
Pindyck, Robert S., 1988. Irreversible investment, capacity choice, and the value of the firm. Am. Econ. Rev. 78 (5), 969–985.
Popp, Aaron, Zhang, Fang, 2016. The macroeconomic effects of uncertainty shocks: the role of the financial channel. J. Econ. Dyn. Control.
Rajan, Raghuram, Zingales, Luigi, 1998. Financial dependence and growth. Am. Econ. Rev. 88 (3), 559–586.
Ramey, Garey, Ramey, Valerie A., 1995. Cross-country evidence on the link between volatility and growth. Am. Econ. Rev. 85 (5), 1138–1151.
Staiger, Douglas, Stock, James H., 1997. Instrumental variables regression with weak instruments. Econometrica 65, 557–586.
Stein, Luke C.D., Stone, Elizabeth, 2013. The effect of uncertainty on investment, hiring, and R&D: Causal evidence from equity options. Working paper.
Surico, Paolo, Haroon, Mumtaz, 2016. Policy uncertainty and aggregate fluctuations. CEPR DP No. 9694.
Tong, Hui, Wei, Shang-Jin, 2011. The composition matters: capital inflows and liquidity crunch during a global economic crisis. Rev. Financial Stud. 24 (6), 2023–2052.