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Aggregate Uncertainty and Sectoral Productivity Growth: The Role of Credit Constraints[°]

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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. This 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 for 25 industries for 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, such as financial development (Rajan and Zingales, 1998) and counter-cyclical fiscal policy (Aghion et al., 2014). The results also hold if economic policy uncertainty (Baker et al., 2015) is used instead of stock market volatility as the measure of aggregate uncertainty.

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I. Introduction

This paper studies the impact of uncertainty on productivity. There has been a revival of interest in understanding the role of uncertainty as a driving force and a propagation mechanism in macroeconomic fluctuations. 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 3 percent within one quarter. Employment and investment fall as firms adopt a 'wait and see' attitude in the face of the increased uncertainty. Total factor productivity (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 related work, 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 more costly (or less efficient) inputs of production, like temporary work, 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.[1]

In a similar vein, Aghion et al. (2010) consider a model where firm can undertake two types of investment: a short-term investment, which contributes to output and liquidity quickly, and a long-term investment, which is more productive but takes longer to complete. When credit

[1] 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 Michie and Sheehan (2003) for evidence from the UK, Kleinknecht el al. (2006) for the Netherlands, Dolado et al (2012) for Spain and 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.

markets are imperfect (that is, when there are credit constraints), the ratio of short-term to long-term investment goes up during a recession, as firms switch to short-term investment in an attempt to maintain output and liquidity. This switch in the composition of investment lowers aggregate growth and productivity. In a subsequent paper, Aghion et al. (2014) and Aghion et al. (2015) use a version of this model to show that exogenous aggregate shocks, such as variations in fiscal policy and monetary policy, affect industry-level growth, and more so in credit-constrained industries. Our paper is in the spirit of the work by Aghion et al (2014) and Aghion et al. (2015). The aggregate shock we consider is not eitherfiscal or monetary policy but uncertainty. However, we share with them the strategy of using of industry-level data to identify better the impact of the aggregate shock and of studying how this impact depends on the characteristics of industries.

Our key finding is that the adverse impact of uncertainty on industry-level productivity growth is greater in industries that rely more heavily on external finance. This result is based on the use of data for 25 industries for 18 advanced economies over the period 1985-2010. 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 of instrumental variables and 'natural experiment' approaches (e.g., 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). Our use of industry-level data for several countries over a reasonably long period of time offers another promising approach. Specifically, the advantages of having a three-dimensional data set (j industries, i countries and t time periods) are three-fold:

- We control for aggregate and country-sector shocks by including country-time (i,t) and industry-country (j,i) fixed effects. The former are particularly important as they allow us to control for any unobserved cross-country heterogeneity in the macroeconomic shocks that affect productivity growth in countries. In a pure cross-country analysis, this would not be possible, leaving open the possibility that the impact attributed to uncertainty was in fact due to other unobserved macro shocks.

- We mitigate 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, particularly if no one industry is a big part of the aggregate. 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.

- We identify non-linearities in the relationship between volatility and TFP growth. The three-dimensional data set addresses the concern by Imbs (2007) that the negative relationship between growth and volatility at the aggregate level can mask a positive relationship at the sectoral level driven by various mechanisms such as precautionary saving, creative destruction, and liquidity constraints. Indeed, we find that the relationship can be both positive and negative at the industry level depending on the degree of credit constraints, thereby reconciling the mixed empirical evidence (Ramey and Ramey, 1995; Martin and Rogers, 2000; Imbs, 2007).

In short, our cross-country/cross-industry difference-in-difference analysis offers considerable advantages over a pure time series or pure cross-country approach. A limitation is that our analysis captures the impact of uncertainty on industry-level productivity growth, rather the aggregate effect. Inferring the impact of uncertainty on aggregate productivity growth from this micro estimate would require some additional assumptions, as for instance done in Stein and Stone (2012) in their study of the effect of uncertainty on investment using firm-level data.

The rest of the paper is structured as follows. Section II provides a literature review. Section III presents the theoretical framework. Section IV discusses the data and empirical methodology. Section V presents our main empirical findings and several robustness checks. Section VI concludes.

II. 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.[2] Recent empirical evidence,

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

mostly using vector-autoregression (VAR) models, tends to find a negative impact of uncertainty shocks on macroeconomic outcomes (Bloom, 2009; Leduc and Liu, 2012; Bachmann et al, 2013; Gourio et al, 2013; Carrière-Swallow and Céspedes, 2013; Caggiano et al., 2014; Choi and Loungani, 2015; Surico and Mumtaz, 2016),the the

We provide empirical evidence that the degree of financial frictions is crucial in shaping the effect of an increase in uncertainty on productivity growth. Our work contributes to the three main stands 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 with a general equilibrium framework (Arellano et al., 2010; Bianchi et al., 2014; Christiano et al., 2014; Gilchrist et al., 2014; Cesa-Bianchi and Corugedo, 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.[3]

The second strand of the literature attempts to resolve the issues of endogeneity and reverse causality between uncertainty and aggregate variables by using disaggregated level 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.[4] Our paper is

[3] Although a few studies (Akinci, 2013; Carrière-Swallow and Céspedes, 2013; Choi, 2015) 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 friction. 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.

[4] 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), Bloom et al. (2007), Julio and Yook (2012), Byun and Jo (2014), Kang et al. (2014), Handley et al. (2015), and Gulen and Ion (2016) study how uncertainty affects firm-level investment and find that the heterogeneous effects of uncertainty

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 to further reduce reverse causality concerns.

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; Obstfeld, 1994; Ramey and Ramey, 1995; Martin and Rogers, 2000; Acemoglu et al., 2003; Imbs, 2007). However, Imbs (2007) emphasized 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 disaggregate 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. Therefore, our findings provide a convincing mechanism to explain why volatility and long-run growth are negatively related.

III. THEORETICAL FRAMEWORK

We provide a simple theoretical framework to formulate the main hypotheses of the paper. As in the models in Aghion et al. (2010) and Aghion et al. (2014), 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 future productivity. Suppose there are two types of investment projects (long- vs. short-term), where the former is riskier but more productive than the latter.[5] 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-

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.

[5] One can think of the former as investment in R&D or human capital which is subject to liquidity risk, as a firm can make very little profit from an early termination of this type of investment. The latter is purchase of an equipment or machinery that can be used as a mode of production instantly.

optimal level. An increase in uncertainty about productivity, when it interacts with credit constraints, exacerbates this problem: , a mean preserving spread of productivity discourages constrained firms from engaging in long-term investment.[6] This channel should be stronger during recessions than expansions as more firms become credit constrained during recessions.

Formally, consider a two-period model in which a measure 1 of risk-neutral entrepreneurs owns a firm. Firm-level productivity $A_{i,t}$ in period t is given by a product of aggregate level productivity a_t and firm-specific level of the human capital (or knowledge) $H_{i,t}$. Each entrepreneur is endowed with the same initial wealth $W_t = wH_t$ ($H_{i,t} = H_t$ for all i). An entrepreneur allocates her wealth between short-term physical investment $K_t = kH_t$ and long-term productivity-enhancing investment $Z_t = zH_t$ in period t, so that $w = k + z$.

There are two types of a shock: an aggregate productivity shock a_t and an idiosyncratic liquidity shock $C_{i,t}$. Following Bloom (2009), we assume that aggregate productivity evolves as an augmented geometric random walk and uncertainty shocks are modeled as time variations in the standard deviation of the driving process.

$$a_{t+1} = a_t(1 + \sigma_t \varepsilon_{t+1}), \tag{1}$$

$$\sigma_t \in \{\sigma_L, \sigma_H\} \text{ and } \varepsilon_t \sim N(0,1),$$

where σ_t is the standard deviation of an aggregate productivity shock and ε_t is an independent and identically distributed (*i.i.d.*) normal shock. Before making its investment decisions, a firm observes the current state of aggregate productivity ($a_t = a$).

Once investment decisions of the entrepreneurs are made, two types of shock (an aggregate productivity shock and an idiosyncratic liquidity shock) occur at the beginning of the period t+1. The short-term investment yields profits $\pi_{t+1} = a_{t+1}k^{\alpha}H_t$, where $0 < \alpha < 1$, while the long-term investment yields profits $v_{t+1}H_t$ at the end of the period $t+1$ with probability λz if the firm survives an idiosyncratic liquidity shock $C_{i,t+1} = c_{i,t+1}H_t,\ c_{i,t} \sim_{i.i.d.} unif(0,1)$ at the beginning of the period t+1. Under risk neutrality and i.i.d. shocks, the timing convention in this paper implies that firms are identical ex-ante. Thus, we focus on a symmetric equilibrium in which all firms choose the identical k and z. The model is highly stylized under the following assumptions given that our objective is to derive the simplest possible theoretical prediction on

[6] With a mean preserving spread in the distribution of a productivity shock, long-term investment is less likely to be successful, making a constrained firm effectively risk averse.

how an increase in aggregate uncertainty affects sectoral productivity growth via financial constraints.

Assumption 1.

The long-term investment is sufficiently productive: $v_{t+1} > \frac{a\alpha}{\lambda} w^{\alpha-1}$.

Assumption 2.

There are two types of firms in this economy. Whereas a fraction of $1-\mu$ *(unconstrained) firms can borrow up to the net present value of their profit, a fraction of* μ *(constrained) firms needs to refinance their project using their own cash flow only*. $0 < \mu < 1$.

Constrained firms survive the liquidity shock if their realized short-term profit is greater than their liquidity cost. Thus, the probability that a constrained firm survives the liquidity shock is $f_{t+1} = \Pr(a_{t+1}k^{\alpha} \geq c) = \min\{a_{t+1}k^{\alpha}, 1\}$ under the uniform distribution of a liquidity shock. A unit mass of total firms in the economy implies that a fraction f_{t+1} of constrained firms will survive the liquidity shock.

Proposition 1.

Unconstrained firms always invest a positive amount of their human capital in the long-term investment, $z_{nc} > 0$ *and their investment is larger than that of constrained firms:* $z_{nc} > z_c$.

Proof.

See Proof 1 in the Appendix.

Lemma 1.

A mean preserving spread of aggregate productivity distribution decreases z_c*, but does not affect* z_{nc}.

Proof.

Proof 1 in the Appendix shows that only z_c *is a function of* σ_t *and* $\frac{\partial z_c}{\partial \sigma_t} < 0$.

We can decompose the growth rate of the TFP into:

$$ln\, A_{i,t+1} - ln\, A_{i,t} = ln\, a_{t+1} - ln\, a_t + ln\, H_{i,t+1} - ln\, H_{i,t}. \tag{2}$$

Under the random walk assumption on the aggregate productivity process, the expected TFP growth rate depends on the fraction of projects that survive the liquidity shocks:

$$g_{t+1} = E\left[\ln A_{i,t+1} - \ln A_{i,t}\right] = \lambda((1-\mu)z_{nc} + \mu z_c \min(a_{t+1}(w - z_c)^{\alpha}, 1)). \tag{3}$$

Lemma 2.

An increase in aggregate uncertainty reduces the expected TFP growth: $\frac{\partial g_{t+1}}{\partial \sigma_t} < 0$.

Proof.

Lemma 1 *and the assumption of* $0 < \mu < 1$ *complete Lemma 2.*

***Lemma 3**.*

An increase in aggregate uncertainty reduces the expected TFP growth more the higher the fraction of constrained firms: $\frac{\partial}{\partial \mu}\left(\frac{\partial g_{t+1}}{\partial \sigma_t}\right) < 0$.

Proof.

Lemma 1 *and Lemma* 2 *complete Lemma* 3*.*

Lemma 4.

The differential effect of an increase in uncertainty is larger when realized productivity is lower:

$\frac{\partial}{\partial a_{t+1}}\left(\frac{\partial}{\partial \mu}\left(\frac{\partial g_{t+1}}{\partial \sigma_t}\right)\right) < 0$.

Proof.

$\frac{\partial f_{t+1}}{\partial a_{t+1}} < 0$ *from Proof* 1 *in the Appendix.*

Lemma 2 implies that an increase in aggregate uncertainty has a negative effect on the TFP growth at aggregate-level, consistent with findings of Bloom et al. (2014). Lemma 3 further suggests that an increase in aggregate uncertainty reduces productivity growth more in industries that are financially constrained, which is our main hypothesis. Finally, Lemma 4 implies that financial constraints bind more in a bad state, so the interaction between an increase in uncertainty and financial constraints on the TFP growth rate is larger in recessions than expansions. We empirically test these theoretical predictions by exploiting cross-industry variation in μ and cross-country and time variation in σ .

IV. Data and Methodology

A. Data

This section provides a description of the main variables used in the empirical analysis: the measures of country-level uncertainty and dependence on external finance. Our data sample covers an unbalanced panel of 25 industries for 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.

Following common practice in the literature (Bloom, 2009; Leduc and Liu, 2012; Bachmann et al., 2013; Carrière-Swallow and Céspedes, 2013; Gourio et al., 2013; Caggiano et al. (2014); Choi and Loungani, 2015), we construct country-specific measures of time-varying uncertainty using aggregate stock market volatility as a proxy. This measure of uncertainty is readily available for long periods and allows for straightforward cross-country comparison.[7] Admittedly, it is not a perfect measure of uncertainty as it can often reflect abnormal behavior in equity markets rather than capture the economic 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. (2015), which are less subject to this criticism.

Specifically, we use realized volatility of aggregate stock market returns from each of the country 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:

$$RV_{i,t} = 100\sqrt{T_i \sum_{s=1}^{T_i} r_{i,s}^2}, \tag{4}$$

where $r_{i,s}$ are daily returns of the stock market *i* from an 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 provide 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.

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[7] 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.

Figure 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. The figure and Table 1 further suggest 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—sectoral level data for TFP (labor productivity) growth are taken from the EU KLEMS and World KLEMS database (for details, see O'Mahony and Timmer, 2009).

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.[8] Figure 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.

Before proceeding to the empirical work, we present some correlations that are present in the raw data using scatter plots. Panel A in Figure 3 plots a relationship between quarterly aggregate uncertainty and the quarterly aggregate utility-adjusted TFP growth for the US economy from 1970 to 2013. Evidence at the aggregate level is consistent with the theoretical prediction of Lemma 2, and Panel B in Figure 3 suggests that the negative relationship also holds in international data. Interestingly, Figure 4 shows a positive (negative) relationship between aggregate uncertainty and the sector-level TFP growth for industries with low (high) external finance dependence, which is consistent with the theoretical prediction of Lemma 3. We further elaborate on this pattern from the raw data in the following section.

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

B. 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:

$$TFP_{i,j,t} = \alpha_{i,t} + \gamma_{i,j} + \beta f d_j U_{i,t} + \varepsilon_{i,j,t}, \tag{5}$$

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 to control 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 to control for 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 for the whole sample—that is, US measures of dependence on external finance may be affected by US-specific regulations or sectoral patterns. However, this is 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 counties, rather than difference across countries' institutional characteristics. For example, if the 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.

Equation (5) is estimated using OLS—and standard errors are clustered at the country-industry level—as the inclusions of country-time and industry-country fixed effects is likely to largely address 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 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.

However, a remaining possible concern in estimating equation (5) with OLS is that other macroeconomic variables could affect sector TFP growth when interacted with industry' 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.

V. RESULTS

A. Baseline results and interpretation

Table 2 presents the results obtained by estimating equation (5). 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 Figure 4. They confirm that the effect of uncertainty on industry TFP growth varies depending on the degree of external financial dependence, and tend to be negative for industries that are relatively more heavily dependent on external finance.

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

B. Robustness checks

This section performs several tests to check whether the results presented above are robust to different specifications, different samples of industries, the inclusion of additional variables to address possible omitted variable bias, different dependent variables as well as an alternative measure of aggregate uncertainty.

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 industry-country fixed effects (Table 2 column II); (ii) or 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, on average, associated with lower industry TFP growth.

In addition, the results are robust when considering the lag of the interaction term between macro uncertainty and sectoral external finance (Table 2, column IV), as well as when using a categorical measure of external finance—which takes value 1 for the sector with the lowest degree of external finance, and 25 for the sector with the largest degree of external finance (Table 2, column V).

Different samples of industries

The theoretical predictions of the effect of uncertainty on TFP growth and the role of credit constrained are likely to be more relevant for manufacturing industries, as these are those characterized by a higher share of R&D 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, equation (5) 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 significantly effect—at least through this channel—on non-manufacturing industries.

Different factors and omitted variable bias

As discussed before, a possible concern in estimating equation (5) is that the results are biased due to the omission of macroeconomic variables affecting TFP growth through the dependence on external finance and 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 equation (5) 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 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 distribution of uncertainty 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.

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 effect materializes is through an increase in inputs of production, notably investment (see, for example, Chapter 3 of the IMF WEO April 2015).

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 heavily 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 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) shows 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; (ii) the budget balance-to-GDP ratio. The results obtained controlling for these variables interacted with dependence on external finance shows 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).

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 control for 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.[9]

The results presented in Table 5 shows 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 distribution of uncertainty 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. This finding helps us understand the mechanism through which volatility affects growth: although a stream of economic theories link volatility to growth

[9] 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.

via investment, Ramey and Ramey (1995) argued that volatility seems play insignificant role in explaining cross-country difference in the investment share of GDP. Our findings corroborate those of Ramey and Ramey (1995) and highlight the role of technology adoption as the main channel through which volatility negatively affects growth.

Alternative uncertainty measure

As an additional robustness check, we re-estimate equation (5) using the economic policy uncertainty index constructed by Baker et al. (2015). Unlike stock market volatility, the economic policy uncertainty index is based on the newspaper coverage frequency of policy-related economic uncertainty. Baker et al. (2015) 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; Pástor and Veronesi, 2014; Choi and Loungani, 2015; Bernal et al., 2016; Gulen and Ion, 2016).

While 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,* its main shortcoming is that it is available for only 10 countries (Canada, France, Germany, Italy, Japan, Korea, the Netherlands, Spain, the UK, and the US) in our sample, and for most only since the mid-90s.[10]

Nevertheless, the results presented in Table 6 shows that the statistically significance of the results is robust to the use of this alternative measure, and the magnitude of the effect is even larger.[11] In particular, the differential TFP (labor productivity growth) loss from an increase in economic policy uncertainty from the 25^{th} to the 75^{th} percentile of distribution of uncertainty for

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[10] 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.

[11] 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.

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.

C. Nonlinearities

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 non-linear and materializes only above a given uncertainty threshold. Using a logistic smooth transition autoregressive model, Jones and Enders (2016) find that the effects of uncertainty shocks on macroeconomic activity are non-linear at the aggregate level. To address this question, we perform two empirical exercises. The first consists of augmenting equation (5) with an interaction term between the square of uncertainty and external financial dependence:

$$TFP_{j,i,t} = \alpha_{i,t} + \gamma_{i,j} + \beta f d_j U_{i,t} + \delta f d_j U_{i,t}^2 + \varepsilon_{i,j,t}. \tag{6}$$

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:

$$TFP_{j,i,t} = \alpha_{i,t} + \gamma_{i,j} + \beta^{U+} f d_j D_{i,t} U_{i,t} + \beta^{U-} f d_j (1 - D_{i,t}) U_{i,t} + \varepsilon_{i,j,t}, \tag{7}$$

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

The results obtained by estimating equation (6) and (7) are reported in Table 7. They suggest that the effect of uncertainty on industry TFP (labor productivity) growth does not significantly depend on the level of uncertainty itself.

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 for this hypothesis, the following equation is estimated:

$$TFP_{j,i,t} = \alpha_{i,t} + \gamma_{i,j} + \beta f d_j U_{i,t} + \delta D_j U_{i,t} + \varepsilon_{i,j,t}, \tag{8}$$

where D is a dummy variables which takes value 1 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.[12]

The results presented in Table 8 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.[13] 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.

D. 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 to 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 follow regression:

$$TFP_{j,i,t} = \alpha_{i,t} + \gamma_{i,j} + \beta^L fd_j F(z_{i,t})U_{i,t} + \beta^H fd_j(1 - F(z_{i,t}))U_{i,t} + \varepsilon_{i,j,t} \qquad (9)$$

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

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 states. Our analysis

[12] Qualitatively similar results are obtained when considering different thresholds, such as the median or the 66th percentile of the distribution of external finance.

[13] 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 1 percent.

uses contemporaneous GDP growth as a measure of the state of the economy.[14] The results presented in Table 9 (columns I and II) suggest that the effects of uncertainty on industry TFP (labor productivity) growth are very different across economic regimes.[15] During 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 significantly different from zero.

In the second approach, we modify equation (9) by replacing $F(z_{it})$ with a dummy that takes value 1 when output gaps are below the historical sample median (-0.3), and zero otherwise.[16] The results obtained by estimating this specification suggests that the effect of uncertainty on TFP (productivity) growth is larger during periods of negative output gaps than positive ones, but larger in the latter case (Table 9, 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.

VI. CONCLUSIONS

Using an extensive international data set and the Rajan and Zinagles (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 productivity growth more in industries that heavily depend on external finance and there is strong asymmetry in the interaction effect between recessions and expansions.

Regarding heightened uncertainty and world-wide 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) and Aghion et al. (20152014) that

[14] Following Auerbach and Gorodnichenko (2012), we use ? $3 = 1.5$ for the analysis of recessions and expansions.
[15] Similar are results are also obtained when the sample period is restricted to 2007, suggesting that they are not driven mainly by the Great Recession.

[16] Estimates of output gaps are taken from the OECD Economic Outlook Database (2015).

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.

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
Netherland	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

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

Explanatory variable	(I)	(II)	(III)	(IV)	(V)
Uncertainty* financial dependence	-4.102***	-2.889***	-2.513***		
	(-3.24)	(-2.98)	(-2.60)		
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
Country*time fe	yes	yes	no	Yes	yes
Country*sector fe	yes	no	no	Yes	yes
Observations	10,654	10,654	10,654	10,654	10,654
R^2	0.55	0.27	0.25	0.55	0.55

Note: estimates based on equation (5). 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.

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

Explanatory variable	(I)	(II)
	Manufacturing	Non-Manufacturing
Uncertainty* financial dependence	-4.423***	-1.107
	(-3.23)	(-0.43)
Differential effect in TFP growth (%)	-2.3	-0.6
Observations	6,612	4,042
R^2	0.57	0.58

Note: estimates based on equation (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. 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 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	9,559	9,459	9,310
R^2	0.55	0.55	0.53	0.53	0.54

Note: estimates based on equation (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. 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 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*** (-3.59)	-2.946*** (-2.81)	-4.220*** (-3.58)	-2.915*** (-2.74)	-3.083*** (-2.82)	-2.400** (-2.15)
Credit to GDP * financial dependence		-0.184*** (-3.13)				-0.153*** (-2.84)
Inflation* financial dependence			0.515 (1.03)			0.513 (0.89)
Government size * financial dependence				0.425 (1.40)		-0.004 (-0.01)
Budget balance * financial dependence					-0.613*** (-2.22)	-0.287 (-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	9,899	9,799	9,310
R^2	0.61	0.62	0.61	0.62	0.62	0.54

Note: estimates based on equation (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. Differential in productivity 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 6. The effect of economic policy uncertainty on TFP and labor productivity growth.

Explanatory variable	(I)	(II)
	TFP growth	Productivity growth
Economic policy uncertainty* financial dependence	-0.081* (-1.62)	-0.093** (-2.03)
Differential effect in TFP growth (%)	-4.0	-4.6
Observations	4,552	4,042
R^2	0.51	0.60

Note: estimates based on equation (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. 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 7. The effect of uncertainty on TFP and productivity growth: testing for non-linearities

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	9,899
R^2	0.55	0.55	0.61	0.61

Note: estimates based on equations (6) and (7). 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 8. The effect of uncertainty on TFP and productivity growth: testing for non-linearities

Explanatory variable	(I)	(II)
	TFP growth	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 equation (8). 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 9. The effect of uncertainty on TFP and productivity growth: the role of business cycle

Explanatory variable	(I)	(II)	(III)	(IV)
	TFP growth	Productivity growth	TFP growth	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 equation (9). 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.

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

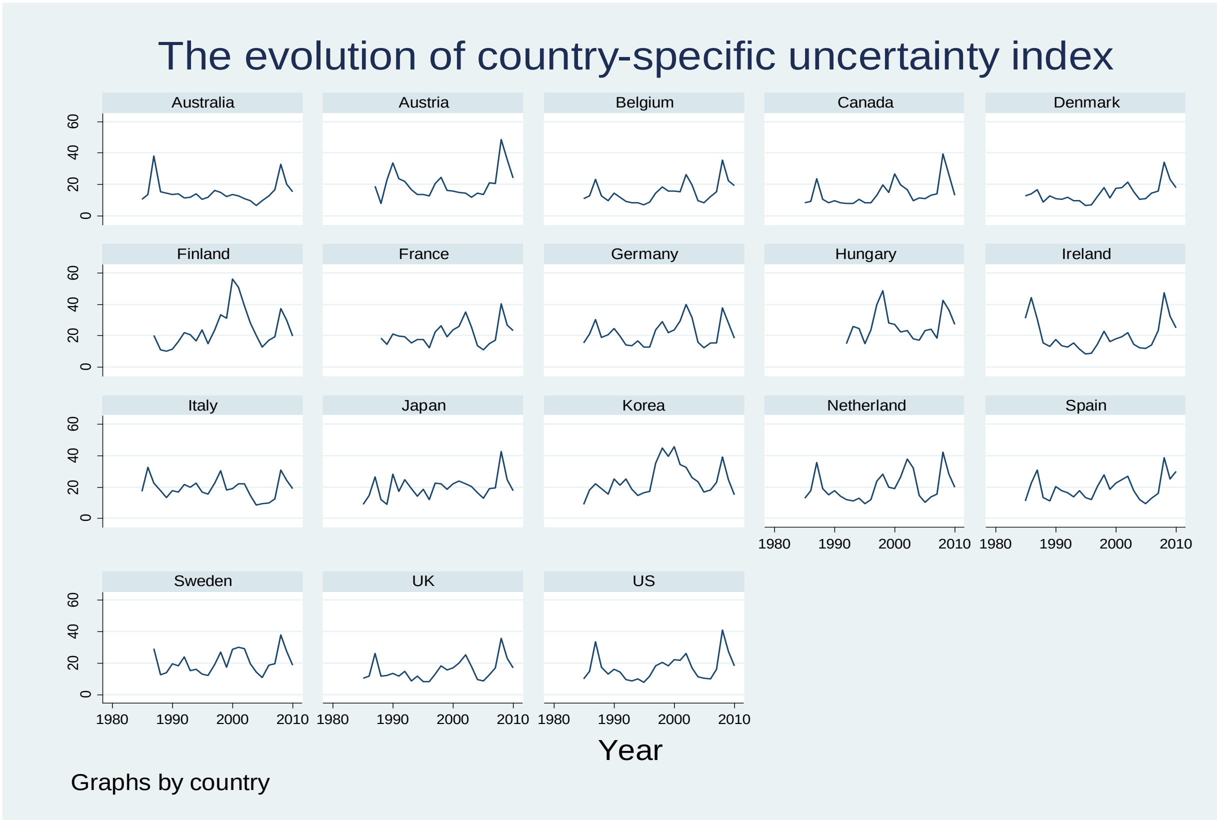
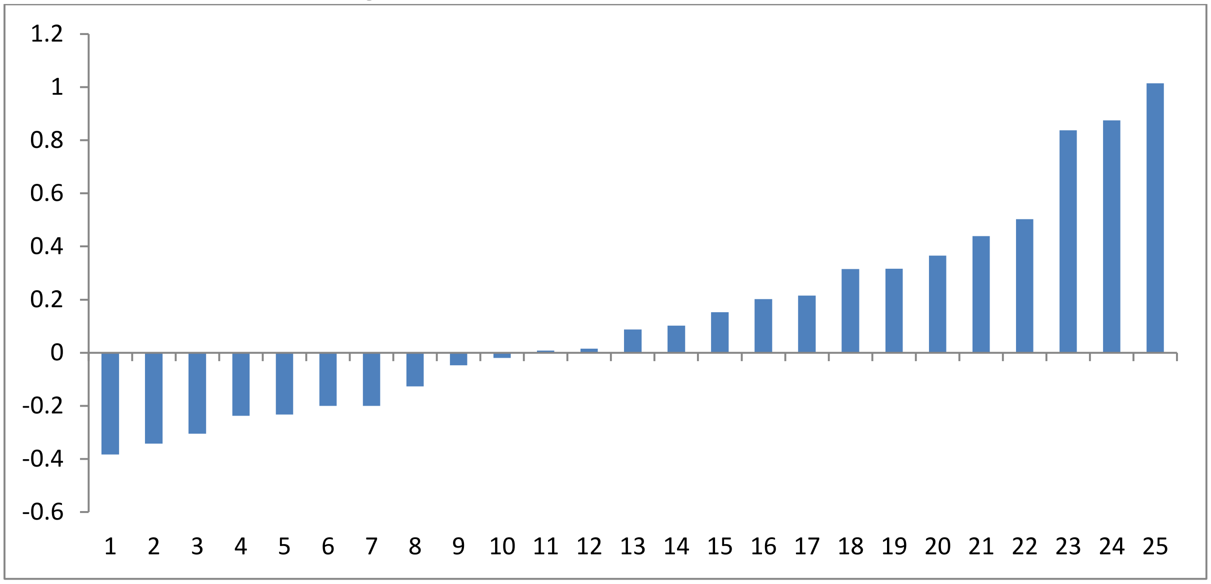


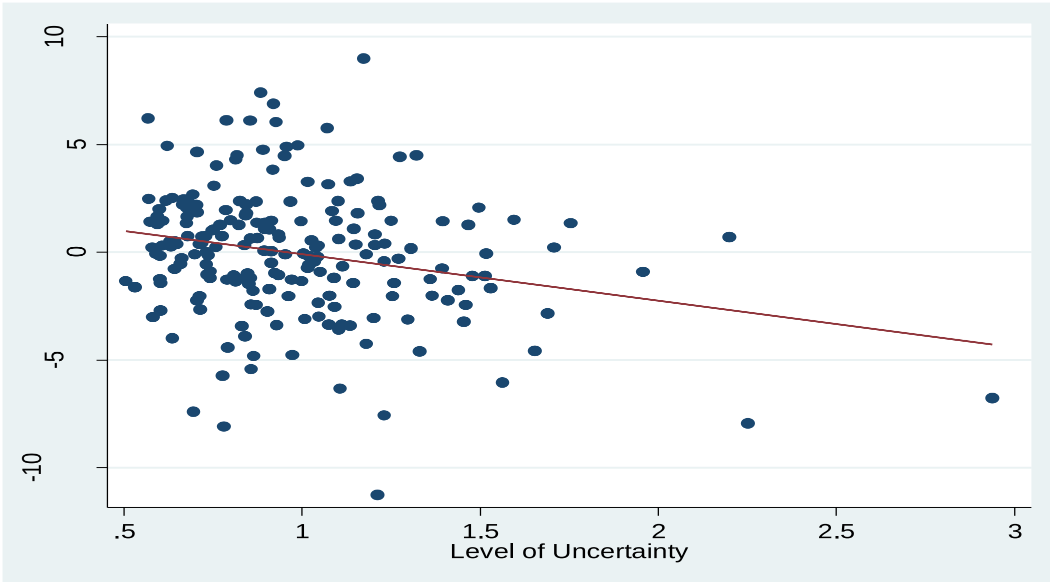
Figure 2. Dependence on external finance



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.

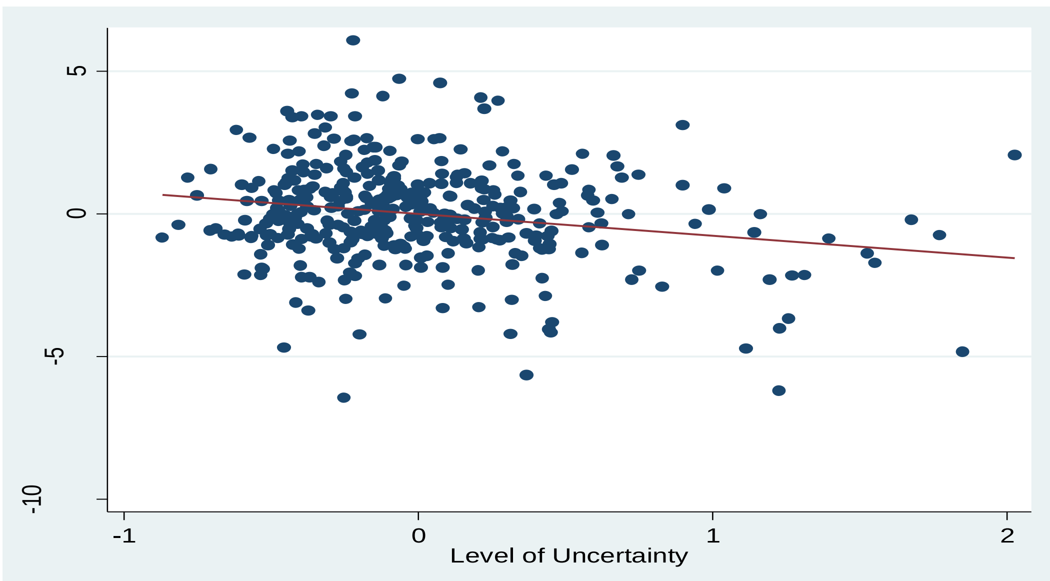
Figure 3. Uncertainty and TFP growth: correlation at the aggregate level.

Panel A. The United States



Coef = -2.16; t-statistics (based on clustered standard errors) = -3.65

Panel B. Sample of 18 advanced economies

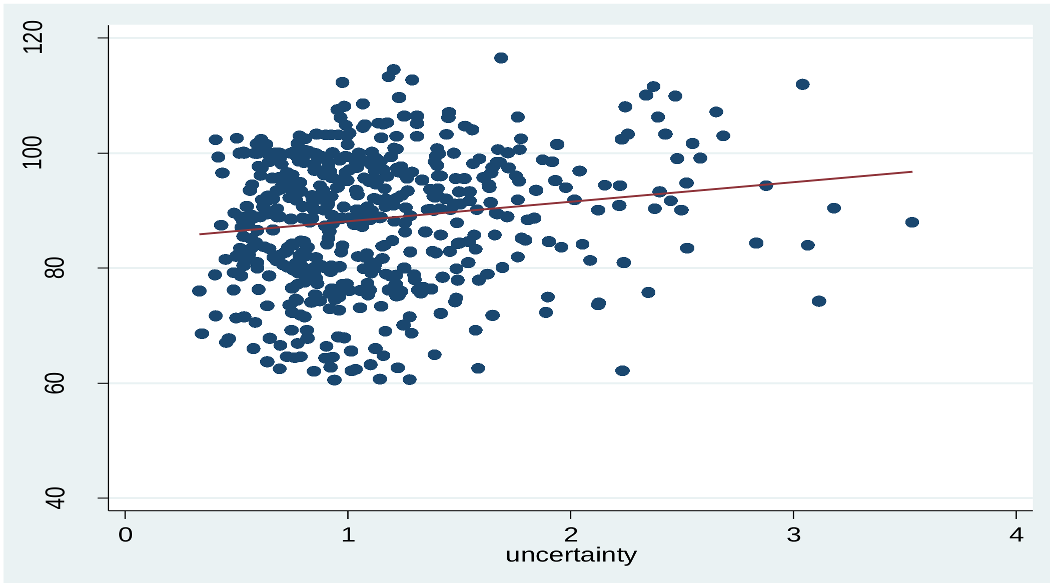


Coef = -0.76; t-statistics (based on clustered standard errors) = -3.51

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).

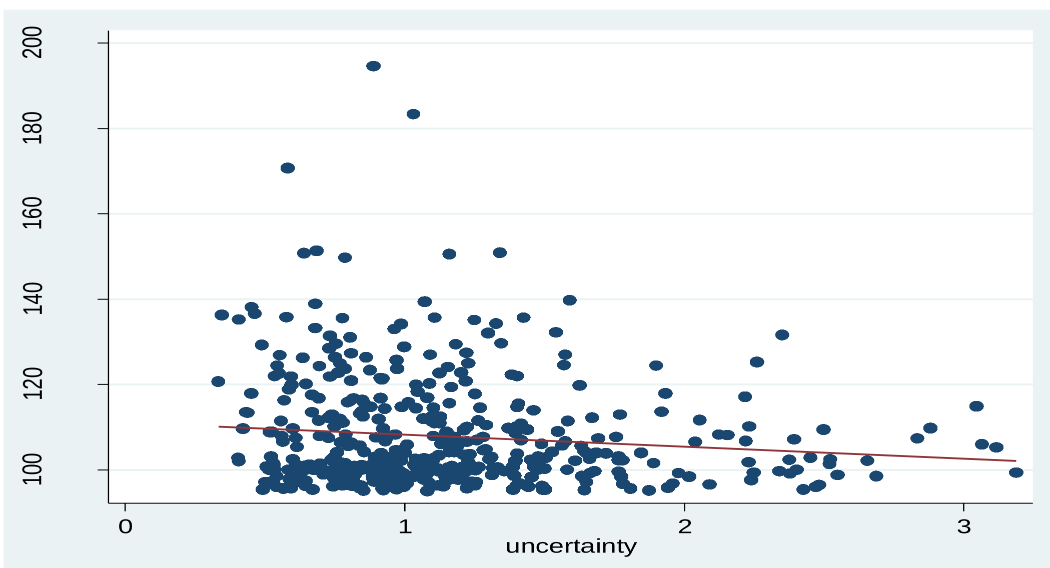
Figure 4. Uncertainty and TFP growth: correlation at the industry level.

Panel A. Industry with below median financial dependence



Coef = 3.4; t-statistics (based on clustered standard errors) = 3.6

Panel B. Industry with above median financial dependence



Coef = -2.8; t-statistics (based on clustered standard errors) = -2.9

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.

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Appendix

Proof 1.

First, an unconstrained firm maximizes its end of $t+1$ consumption by choosing k and z after observing $a_t = a$:

$$\max_{k,z} E_t[a_{t+1}k^{\alpha}H_t + \lambda z V_{t+1}H_t | a_t = a], \tag{A.1}$$

subject to $k + z = w$.

One can rewrite A.1 as

$$\max_{k,z} (a(w-z)^{\alpha} + \lambda z V_{t+1})H_t \tag{A.2}$$

Maximization of A.2 leads to

$$z_{nc} = w - \left(\frac{\lambda}{\alpha a} v_{t+1}\right)^{\frac{1}{1-\alpha}},$$

which is strictly positive from Assumption 1.

Second, a constrained firm maximizes its end of $t+1$ consumption by choosing k and z after observing $a_t = a$:

$$\max_{k,z} E_t[a_{t+1}k^{\alpha}H_t + f_{t+1}\lambda z V_{t+1}H_t | a_t = a], \tag{A.3}$$

subject to $k + z = w$.

One can rewrite A.3 as

$$\max_{k,z} a(w-z)^{\alpha}H_t + E_t[f_{t+1}\lambda z V_{t+1}H_t | a_t], \tag{A.4}$$

where $f_{t+1} < 1$ and $\frac{\partial f_{t+1}}{\partial \sigma_t} < 0$ under reasonable assumptions on the support of *a*, *k*, and *c*.

Maximization of A.4 leads to,

$$z_c = w - \left(E_t[f_{t+1}]\frac{\lambda}{\alpha a} v_{t+1}\right)^{\frac{1}{1-\alpha}}.$$

Because $f_{t+1} < 1$ and $0 < \alpha < 1$, $z_{nc} > z_c$.

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