Gray's Anatomy: Understanding Uncertainty

Samaniego, Roberto and Sun, Juliana

George Washington University, Singapore Management University

13 July 2016

Gray's Anatomy: Understanding Uncertainty

Roberto M. Samaniego* Juliana Y. Sun†

July 13, 2016

Abstract

We explore the key mechanisms whereby uncertainty impacts the business cycle by exploring the interaction of uncertainty with growth in industries with different technologies of production. We find that uncertainty shocks are particularly detrimental to growth in industries with rapid capital depreciation or high investment adjustment costs. The findings are consistent with real options theory: uncertainty leads firms to delay investment in new projects, but high depreciation and fixed costs of investment make delay more costly. On the other hand, we do not find evidence of a significant role of financial markets in the generation nor propagation of uncertainty shocks.

Keywords: Uncertainty, technology, industry growth, depreciation, capital adjustment costs, investment lumpiness, real options.

JEL Codes: D81 E22 E32.

*Roberto M. Samaniego, George Washington University, 2115 G St NW Suite 340, Washington, DC 20052. Tel: (202) 994-6150. Fax: (202) 994-6147. Email: roberto@gwu.edu.

†Juliana Y Sun, Singapore Management University, 90 Stamford Road, Singapore 178903. Tel: (65) 6808 5456. Fax: (65) 6828 0833. Email: yusun@smu.edu.sg.

Veritas visu et mora, falsa festinatione et incertis valescunt.

"Truth is confirmed by inspection and delay; falsehood by haste and uncertainty."

Tacitus, Annales Liber Ii 39.

1 Introduction

Recent evidence identifies second-moment shocks – often simply called "uncertainty" – as a key determinant of the business cycle. However, the key sources and propagation mechanisms of uncertainty remain a topic of debate. Resolving this debate is key for identifying the empirically relevant class of model for understanding the macroeconomic impact of uncertainty.

This paper explores the key sources and propagation mechanisms that lead uncertainty to affect the business cycle. We do so by exploring which *technological characteristics* lead *industries* to grow asymmetrically in times of higher uncertainty. Our aim is to explore the link between industry growth and aggregate uncertainty in a systematic way so as to identify the empirically relevant class of theory for modeling the macroeconomic impact of uncertainty.

The motivation behind our exercise is as follows. The technology of production varies across industries based on factors such as the intensity with which different inputs are used, the properties of those inputs, and so on. If a given technological characteristic interacts systematically with the factors that lead to changes in uncertainty, or if it is one that becomes harder to adjust in times of uncertainty, then growth in industries with that technological characteristic will be more sensitive to changes in measured uncertainty. This indicates that the characteristic in question tells us about the key sources or mechanisms linking uncertainty with growth. On the other hand, if this is not a factor that interacts with uncertainty, or if this is an easily adjusted factor in the production function, no such sensitivity will be detected, indicating this characteristic is not empirically important for uncertainty. As a result, any measurable interaction between an industry technological characteristic and a measure of uncertainty is a diagnostic as to where to look to understand the sources or macroeconomic impact of uncertainty.

Our exercise requires a definition of "technology." Since the work of Kydland and Prescott (1982), theoretical business cycle analysis is commonly performed within the context of models of economic growth. We follow the conventions of growth theory by defining "technology" in terms of the production function. We identify industry differences in the production technology using factor intensities, or using the qualitative attributes of factors of production, an approach that dates back to at least the seminal work of Cobb and Douglas (1928). For example, differences between the technology for producing Food Products (ISIC 311) and the technology for producing Transport Equipment (ISIC 381) can be described in terms of the former being less R&D intensive and less labor-intensive than the latter. Our technology indicators include measures of labor intensity, human capital intensity, R&D intensity, intermediate intensity, asset fixity, capital depreciation, the industry rate of investment-specific technical progress, and the specificity of the inputs used in each industry. We measure them using US data, employing the assumption in Rajan and Zingales (1998), Ilyina and Samaniego (2011) and others that observed technological choices in the United States are indicative of how firms would organize their production in a relatively undistorted and unconstrained environment – an assumption we discuss in detail.

We find robust evidence of an interaction between bond market uncertainty and *the rate of capital depreciation* as well as the *lumpiness of investment* specific to each industry. We do not find robust evidence of any other interactions. The fact that uncertainty interacts with these two industry variables is consistent with the real options literature, e.g. Bernanke (1983), or Dixit and Pindyck (1994). When growth opportunities are uncertain and irreversible, there is an option value to waiting for better information before adopting a growth opportunity. If the depreciation rate of capital invested in current opportunities is high, this will make waiting for information about growth opportunities more costly, leading firms to invest earlier before information about whether projects are worth pursuing is revealed. Similarly, Cooper et al (1999) and others view the lumpiness of investment as evidence of fixed investment costs, which would also make delay costly because depreciating capital might not be replaced because of the fixed cost.

Furthermore, this interaction occurs when we measure uncertainty using *bond market volatility*. This measure captures uncertainty concerning safe assets, i.e. economy-wide uncertainty, indicating the undiversifiable or unhedgable portion of uncertainty. We refer to this as *systemic* uncertainty. Our finding suggests that systemic uncertainty has a negative impact on economic growth because fixed costs of investment and investment irreversibilities optimally require firms to wait for uncertainty to be resolved, but in addition where waiting is costly firms may be pressed into hasty investment or disinvestment.

In addition, we explore whether our industry-based strategy finds evidence of any important role for financial markets in either the origination or propagation of uncertainty shocks, a key question in the literature.[1] We do so in two ways: by including a measure of *external finance dependence* (Rajan and Zingales (1998)) in our list of technological variables, and by conditioning on an interaction of technology with financial crisis indicators (Laeven and Valencia (2013)). We do not find any significant interaction between external finance dependence and uncertainty.[2] In addition, the technology-crisis interactions are not significant, nor do they affect our findings concerning the link between technology and uncertainty. Thus, our results do not support a key role for financial markets in the macroeconomic impact of uncertainty shocks. This is not to say that uncertainty does not cause financial market turmoil, nor that financial markets are never the source of uncertainty shocks: still, in a comprehensive data set covering several decades and countries, we do not find evidence that there are essential or common features of how uncertainty shocks affect the macroeconomy.

Our research exercise is comprehensive. First, we use as many countries and years of data as possible. Second, we use a large set of technological measures, drawn from the related literature on the link between industry growth and macroeconomic outcomes.[3] Third, we use three different measures of industry growth, as well as various other measures of industry performance to narrow down the *channels* whereby uncertainty affects industry growth. Fourth, we use four different measures of uncertainty, drawn from Baker and Bloom (2013). As a result our conclusions have broad relevance. A limitation is that we use manufacturing industry growth data. This is partly because of the difficulty of identifying large cross-country data sets with service sector data, but also because manufacturing data are readily available for purposes of extension or replication, and can be easily aggregated to draw implications for aggregate growth. Naturally a study using a broader set of industries would be a useful extension.[4]

Section 2 explains the motivation behind the exercise and outlines the empirical strategy. Section 3 describes the data and Section 4 delivers the empirical findings. Section 5 concludes.

[1] See for example Arellano et al (2012) or Gilchrist et al (2014).

[2] We also look at R&D intensity, which Ilyina and Samaniego (2011, 2012) link to external finance dependence.

[3] See Rajan and Zingales (1998), Braun and Larrain (2005), Ilyina and Samaniego (2011) and Samaniego and Sun (2015).

[4] It is worth noting, however, that some authors argue that one should exercise caution when performing industry growth regressions by pooling data from different sectors or at different levels of aggregation. This is becase the link between industry growth and its technological determinants (such as productivity growth) varies depending on the elasticity of substitution between goods - see Samaniego and Sun (2016). Within manufacturing, the elasticity of substitution is thought to be more than one – see Anderson and Van Wincoop (2004) and Ilyina and Samaniego (2012). Across broad sectors, however, it is generally thought that the elasticity of substitution is less than one – see Herrendorf et al. (2013). Thus, mixing goods from different sectors or at different levels of aggregation may not be appropriate for an industry growth study.

2 Motivation and Methodology

There are two reasons why particular industries might be more sensitive to uncertainty. One is because the shocks that drive uncertainty particularly affect them. The other is because there are propagation or amplification mechanisms for these shocks that particularly affect certain industries.

2.1 Sources of uncertainty

Theories regarding the sources of uncertainty can broadly be classified as *real, nominal* or *financial.* If the source of uncertainty is *real*, then we might expect industries to be sensitive to uncertainty to the extent that their technology of production is tied to the underlying technological source of real uncertainty. For example, suppose that uncertainty is driven by real variables, such as changes in the variance or dispersion of Hicks-neutral (labor augmenting) productivity shocks, as in the theory of Bloom et al (2012). In this case we might expect labor-intensive industries to be particularly susceptible to changes in uncertainty. If uncertainty concerns the pace of *investment-specific technical change* (ISTC, see Ma and Samaniego 2016), we would expect this to show up in high-ISTC industries. Alternatively, since Greenwood et al (1988) show that capacity utilization is a key determinant of the propagation of ISTC shocks, ISTC uncertainty might particularly affect industries where capital adjustment costs are high, as utilization rather than investment will be a key channel of adjustment to shocks in such industries. If the unpredictable pace of fundamental technical progress is the source of uncertainty, we would expect R&D-intensive or human-capital intensive industries to be more sensitive to uncertainty. On the other hand, if *nominal* uncertainty is key – the volatility or dispersion of prices, as suggested by Oi (1961) – then we would expect to observe a strong reaction of prices during periods of uncertainty, and a particularly strong reaction in industries that user intermediate goods intensively. Finally, if the source of uncertainty is *financial*, then we would expect industries where the need for external funds is particularly high to be sensitive to uncertainty shocks.

2.2 Mechanisms of uncertainty

Perhaps uncertainty has many sources in different places and at different points in time. Still, regardless of the origin of uncertainty, there may be key *propagation mechanisms* that lead uncertainty to have a macroeconomic impact. Depending on the mechanism, this may imply an asymmetric impact of uncertainty on industry growth. For example, real options theory suggests that industries where investment is subject to fixed costs of adjustment might grow slowly when uncertainty is high because they prefer to defer investment until uncertainty is resolved.

More broadly, the survey of Bloom (2014) describes four theories behind the macroeconomic impact of uncertainty, each of which might interact with different aspects of the production technology:

1. *Real options*: when starting or ceasing new business projects is subject to fixed costs or to irreversibilities, greater uncertainty induces caution among firms. This could lead to declines in production for several reasons. One is that potential growth projects may be delayed pending the resolution of uncertainty. Another is that industries where waiting is more costly (e.g. because maintaining current projects is costly due to high capital depreciation) may suffer more, since they may be forced to act before the uncertainty has been resolved. In addition, increased caution in the face of uncertainty may lead firms that should contract or expand based on their changing productivity to *wait*, slowing reallocation of resources among heterogeneous firms and lowering aggregate productivity. See Bernanke (1983) and Dixit and Pindyck (1994) among others. In this case we would expect to observe these industries also displaying low productivity.

2. *Risk aversion*: when firms are risk averse, greater uncertainty (including a greater risk of default) may lower economic activity by increasing the cost of external funds. See for example Gilchrist et al (2014). In this case we would expect uncertainty to have a negative impact on growth, but particularly in industries with high external finance dependence.

3. *Growth options*: on the other hand, when reversion to an old project is easy, greater uncertainty increases the value of trying a new project, without increasing the downside risk (since this can be avoided by simply reverting), leading firms to act as though they were risk-*loving*. Kraft et al (2013) find evidence of this effect in asset prices of R&D intensive firms. In this case, we would expect industries where growth opportunities are greater to grow particularly *fast* when uncertainty is high – be it labor-intensive, high-ISTC, high-human capital or high-R&D industries, depending on the ultimate sources of growth and of uncertainty.

4. *Oi-Hartman-Abel effects*: Some authors have argued that uncertainty can increase growth because, by expanding when outcomes are good or contracting when outcomes

are bad, again firms may behave as though they are risk-*loving* rather than risk averse in the face of uncertainty. See Oi (1961), Hartman (1972) and Abel (1983). These effects are distinct from growth options because they do not involve switching between new and old projects, rather they involve changes in the scale of production of current projects. This is more likely to be observed in industries where adapting to changing conditions is simple, so we would expect to observe relatively slow growth (compared to the average) where flexibility is low e.g. where capital depreciates rapidly or where assets such as capital or knowledge are firm-specific. This is similar to the industries that would suffer in a world where real options are important.

The first two theories, which hinge on some inflexibility at the firm level to adjust to uncertainty, imply that uncertainty leads to contractions in business activity. Thus, we refer to real options and risk aversion as *contractionary* theories of uncertainty. On the other hand, the last two theories hinge on the *flexibility* of firms to adapt to uncertainty, and imply the that uncertainty leads to expansion. We refer to growth options and Oi-Hartman-Abel effects as *expansionary* theories of uncertainty. Of course, given that uncertainty shocks and first moment shocks may often coincide, it is difficult to isolate the effect of uncertainty using aggregate data: this is what motivates our study using industry data instead. Furthermore, each theory has implications for which *kind* of industry we would expect to see expanding or contracting more in times of uncertainty. For example, if real options theory is important for understanding the uncertainty-business cycle link, we would expect industries where adjustment costs of investment are relatively large to display greater sensitivity to uncertainty. If risk aversion is an important channel for uncertainty to affect growth, we should observe a decline in growth particularly in industries that have greater need or more limited ability to raise external funds.

To summarize, we classify theories of uncertainty according to

1. whether the source of uncertainty is real, nominal or financial;

2. whether the propagation mechanism for uncertainty is contractionary or expansionary, each of which comes in 2 varieties.

Thus, we have a matrix of 12 potential classes of theory of the macroeconomic impact of uncertainty. The objective of this paper is precisely to use differences in growth across industries with different technological characteristics as a way to identify which of this twelve classes of theories are empirically more relevant for understanding how uncertainty affects macroeconomic dynamics. In what follows we outline an empirical strategy for detecting the disproportionate impact of uncertainty on industry growth based on technological factors.

We propose to distinguish between these theories by studying the relationship between uncertainty and *industry* growth. The logic is as follows. An extensive literature documents systematic difference in the technology of production across industries. Each theory of uncertainty has implications for which kind of industry – based on their technology of production – should interact most with uncertainty, and whether this interaction is positive or negative. Ordering industries according to a particular technological characteristic, we should be able to determine whether industry growth in industries with that characteristic disproportionately interacts with uncertainty or not, thus telling us which theories are or are not empirically relevant for understanding the impact of uncertainty on growth. If a given characteristic does not interact with uncertainty, then theories that emphasize that characteristic are not empirically relevant – either because that theory is not quantitatively important compared to others, or because the characteristic is easily adjustable so that the mechanism in that theory does not impose binding constraints on firms.

Ideally to implement this strategy, we should use a large set of technological characteristics, as well as several measures of industry performance. We also need to condition on general factors that affect industry growth, other than the technology-uncertainty interactions of interest. Since we seek to identify differential behavior of growth across industries, that means we need to condition on the overall growth impact of first- and second-moment shocks as well. As a practical matter, as well as for our findings to have global generality, we also wish to use as large a sample as possible by pooling data from many countries, since significant uncertainty shocks are likely not very common in any given economy. In what follows we detail our strategy for implementing this procedure.

This is not to say that the only way to identify technology-uncertainty interactions is to use industry data. An alternative strategy for using disaggregated rather than aggregate data would be to use a large firm level dataset to perform a similar exercise. We do not do so for several reasons. One is coverage: whereas some related work on uncertainty does look at firm level data, these are generally for publicly traded firms only, which for many countries may be only a small share of business activity and which could be subject to selection bias because the decision of whether or not to trade publicly is presumably one which could be affected by uncertainty. Furthermore, the set of firms in any data set is endogenous in the sense that country- or date-specific factors (including uncertainty) may skew the composition of a firm-level dataset so that, if technological characteristic X hurts firms for some reason in uncertain times, X-intensive firms may simply shut down and exit the dataset. With industries this will not be a problem, however, since if characteristic X is important and difficult to adjust then X-intensive industries will grow slowly and the exit of X-intensive firms would be detected as slower industry growth. This is also a reason why, when measuring technological characteristics at the industry level, we will want to find an industry index that does not vary across countries or dates. To the extent that there is some heterogeneity in the technology of production, industries with a technological feature that suffer during periods of uncertainty may display that feature less in uncertain times because (as mentioned) firms who have that feature the most may exit the dataset. Instead, we would require a measure of technology that affects all firms, and which is held constant across firms and indeed across countries. Again, if a technological characteristic is easily adjusted or is not relevant for uncertainty then it will simply not be identified as being empirically important by our procedure. That said, an appropriate study using firm level data set would make an interesting complement to our research.

2.3 Econometric specification

Our objective is to see which technological characteristics lead industries to be more sensitive to uncertainty shocks. To do so, we estimate the following equation:

$$\begin{aligned} Growth_{c,i,t} = {} & \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \beta_1(LevelShock_{c,t} \times X_i) \\ & + \beta_2(UncertaintyShock_{c,t} \times X_i) + \beta_3 Controls_{i,c,t} + \epsilon_{c,i,t} \end{aligned} \tag{1}$$

In equation (1), $Growth_{c,i,t}$ is a measure of growth in industry i in country c at date t. The dummy variables $\delta_{i,c} + \delta_{i,t} + \delta_{c,t}$ capture all date- or country-specific factors that might affect growth in industry i, or factors affecting growth in country c at a particular date. All that remains are factors that specifically affect growth in industry i in country c at date t.

X_i is a technological factor of interest that characterizes the production function of industry i, and which is hypothesized to interact with uncertainty. It appears in equation (1) interacted with $UncertaintyShock_{c,t}$, which is a second-moment shock, an indicator of uncertainty. Thus the coefficient β_2 is the differential impact of industry characteristic X_i on industry growth when uncertainty is high. We identify the underlying technological determinants of difficulty in uncertain periods by seeing which technological characteristics display a significant interaction coefficient β_2.

Since β_2 captures the difference in industry growth in uncertain times relative to normal times for industries with different levels of X_i, $\beta_2 < 0$ indicates that growth in industries with high X_i is more seriously affected by uncertainty. For example, if X_i measures the depreciation rate of capital, then $\beta_1 < 0$ would indicate that industries that use rapidly depreciating capital grow particularly *slowly* when there is uncertainty. Conversely $\beta_1 > 0$ would indicate that such industries grow particularly *fast* when there is uncertainty.

The variable $LevelShock_{c,t}$ is a country- and year-specific measure of the level of economic activity. We interact it with the technological variable X_i also because, as is well known in the literature, increases in uncertainty may coincide with (or even cause) downturns in economic activity. Thus we wish to condition on first moment measures of the level of economic activity. The overall level is already captured by the dummy $\delta_{c,t}$, so the coefficient β_1 captures any residual industry-specific impact that level shocks (including the impact of uncertainty shocks on levels of overall economic activity) on industry growth based on technological measure X_i.

This argument raises the possibility of endogeneity of growth and uncertainty: the level and uncertainty shocks may be correlated and also endogenous. One way we handle this is precisely by looking at industry growth rather than aggregate growth. Any omitted variables that cause both growth and uncertainty (as well as level shocks) should be picked up by the $\delta_{c,t}$ indicators, including the level effects. This was precisely the original motivation in Rajan and Zingales (1998) for adopting a differences-in-differences specification such as that in specification (1). In addition, we condition on possible interactions of level effects and the technological variables. We also deal with the possibility of any residual endogeneity in *industry* growth by using instrumental variables, as suggested in Baker and Bloom (2013) in the context of aggregate growth.[5] In this case both level and uncertainty shocks would need to be instrumented. Given a set of instruments for the level and moment shocks $Instr\,(c,t)$, the instruments to be used when the dependent variable is an *interaction* with the level and moment shocks as in specification (1) are $Instr(c,t) \times X(i)$, see Wooldridge (2002).

Some comments on our estimation strategy are in order. First, we seek industry technological indicators X_i that are representative of the technology of production across countries. Suppose for example that X_i represents labor intensity. It is important to underline that we do *not* seek to measure the *observed* labor intensity at firms in industry i around the world, or in each country or at each date. For example, observed labor intensity is not a technological variable, as it will be affected by current economic conditions such as the state of uncertainty or the state of the business cycle at date t in country c, or by financing or other

[5] The instruments are exogenous "disasters", as described in detail below.

institutional frictions that could distort firm behavior in country c. We seek a benchmark measure of labor intensity that firms in industry i would adopt in a relatively undistorted environment – which, when distorted by economic conditions in country c and/or at date t, might lead to particular difficulty to firms in industry i.[6] Following the related literature, we will measure the technological variables X_i using US data and where possible using data on publicly traded firms in the US, whose technological choices are unlikely to be distorted by financing difficulties or by other frictions. We return to this issue when we define our technological measures X_i.

Second, since the number of group-specific effects in this estimation equation is very large,[7] the computational cost of estimating (1) is significant. Instead, we proceed by subtracting from all dependent and independent variables the mean value for each (c, t), (i, t) and (c, i) pair so that the individual specific effects $\delta_{i,c}$, $\delta_{i,t}$ and $\delta_{c,t}$ are removed from the estimation equation. We call these variables $\widehat{Growth}_{c,i,t}$, $(\widehat{LevelShock}_{c,t} \times X_i)$, $(\widehat{UncertaintyShock}_{c,t} \times X_i)$ and $\widehat{Controls}_{c,i,t}$. Then, we estimate (1), using the de-meaned variables, and without $\delta_{i,c} + \delta_{i,t} + \delta_{c,t}$ among the regressors. This yields the following specification:

$$\widehat{Growth}_{c,i,t} = \beta_1(\widehat{LevelShock}_{c,t} \times X_i) + \beta_2(\widehat{UncertaintyShock}_{c,t} \times X_i) + \beta_3\widehat{Controls}_{i,c,t} + \epsilon_{c,i,t} \tag{2}$$

The exact error structure for this procedure is not known so we use a variety of approaches to estimating this modified equation (2), finding that the results are robust. These methods include bootstrapping, allowing for heteroskedasticity using the Huber-White method, clustering by industry, and allowing for autocorrelated errors.[8] The results reported use bootstrapped errors.

Finally, recall that we also require the estimation of (1) using instrumental variables. We use the well known 2SLS approach to instrumental variables estimation. This involves regressing the endogenous dependent variables on the others, including dummies and instruments. We must thus modify the demeaned specification (2) so as to implement the 2SLS

[6] Of course, any impact of country-specific conditions on industry i or of country-specific conditions at date t would be absorbed by the $\delta_{c,i}$ and $\delta_{c,t}$ indicators respectively.

[7] Since there are about 60 countries, 28 industries and 42 years, we would have over 50,000 fixed effects in a balanced panel.

[8] Bertrand et al (2004) argue that differences-in-differences specifications may suffer from problems with autocorrelated errors. However this relates to specifications where there is a persistent treatment vs. non-treatment variable. In our contect there is no such problem because of the constellation of country-time and industry-time dummies. When we estimate the specification allowing for autocorrelated errors the autocorrelation coefficient is small, around 0.01.

procedure. Since the 2SLS procedure requires that the large number of dummy variables should be included at both stages, we implement the demeaning procedure at both stages in order to deal with them.

3 Data

3.1 Defining Uncertainty

We measure uncertainty using the observed volatility of indicators of economic activity or of economically useful information, e.g. Baker and Bloom (2013). Such measures either define uncertainty as the volatility of these measures, or implicitly define uncertainty as the inability to forecast economically important series. For example, if intra-year stock market volatility is the measure of uncertainty, it also admits an interpretation in terms of unforecastability of economically important developments since, according to standard theories of asset pricing, the volatility of stock prices indicates volatile information.

Jurado et al (2015) interpret uncertainty strictly as *unforecastability* and try to measure uncertainty in terms of the component of macroeconomically important measures that is unforecastable based on a wide array of time series. We do not adopt this approach to measuring uncertainty as such an approach requires a large set of time series to identify unforecastable events, which would be challenging to perform in a consistent manner for many countries. In any case, we find that the Jurado et al (2015) measure of uncertainty is highly statistically significantly correlated to the four uncertainty measures we use for the US.[9]

We adopt four measures of uncertainty and economic activity, drawing from Baker and Bloom (2013).[10] In each case, there is a measure of uncertainty based on second moment shocks, and a corresponding measure of first moment shocks.

1. Stock Market Data: The first moment shock is the annual cumulative stock market return, using the broadest general stock market index available for each country, from the Global Financial Database. Uncertainty over the year is the average quarterly standard deviation of daily stock daily returns.

[9]The annual macroeconomic uncertainty series of Jurado et al (2015) at a quarterly frequency has a correlation with the four series Baker and Bloom (2013) we use below computed at similar frequency of between 0.27 and 0.56, statistically significant at the 1 percent level in all cases.

[10]Baker and Bloom (2013) also use a measure of uncertainty based on forecaster disagreement: however we do not have these data for enough countries to make our panel strategy useful.

2. Cross Sectional Firm Data: The first moment shock is the average firm-level stock return, from the WRDS international equity database. Uncertainty is the average quarterly standard deviation of returns.

3. Bond Yield Data: The first moment shock is the average daily 10-year Government bond yield. Uncertainty is the average quarterly volatility of daily percentage changes in bond yields.

4. Exchange Rate Data: The first moment shock is the average daily exchange rate from the Global Financial Database. Uncertainty is the average quarterly volatility of daily percentage exchange rate changes.

Rather than viewing them as different measures of uncertainty (i.e. different approaches to capturing the same thing), we view them as capturing different *kinds* of uncertainty. For example, equity contracts are generally thought of as being subject to greater potential asymmetric information problems than debt (see Jensen and Meckling (1976) and more recently Hérbert (2016)), and most kinds of debt are likely to be safer than equity because of the payments being fixed except in case of default. Thus, stock market volatility captures uncertainty concerning risky investments, whereas changes in cross sectional dispersion reflect changes in the variation of uncertainty concerning different investments. Bond market volatility we view as capturing uncertainty concerning safe assets, possibly indicating the undiversifiable or unhedgable portion of uncertainty, including economy-wide uncertainty e.g. uncertainty stemming from the sovereign's policy or default decisions. We refer to this as *systemic* uncertainty. Finally, exchange rate uncertainty concerns uncertainty from international sources, or changes in the dispersion of uncertainty across countries. Of course these types of uncertainty are not completely orthogonal e.g. volatility of concern about sovereign default will influence exchange rate and stock market volatility. and vice versa if a government-funded bailout is expected.

3.2 Instrumental variables

As mentioned, there is some concern in the literature that level shocks and second moment shocks (uncertainty) could be jointly determined. This is one of the motivations behind our differences-in-differences specification with a complete constellation of (i, c), (i, t) and (c, t) dummy variables: any endogeneity between aggregate first and second moment shocks is irrelevant, only effects that are specific to industries in a particular country in periods of uncertainty such as the interaction of second moment shocks and technology will be picked up by our industry-level interaction coefficients of interest. This is also the motivation behind this methodology, introduced by Rajan and Zingales (1998), albeit in a context without a time panel.

We also account for endogeneity by using a standard instrumental variables procedure. We employ instruments that have been found to be useful in the related literature. Specifically, Baker and Bloom (2013) use a measure of exogenous "disasters" as instruments. The details are in their paper, including details of checks on the exogeneity of these measures, but broadly "disasters" include:

1. Natural Disasters: Extreme weather and geological events as defined by the Center for Research on the Epidemiology of Disasters (CRED). Industrial and transportation disasters are not included.

2. Terrorist Attacks: high casualty terrorist bombings as defined by the Center for Systemic Peace (CSP).

3. Political Shocks: An indicator for successful assassination attempts, coups, revolutions, and wars, from the Center for Systemic Peace (CSP) Integrated Network for Societal Conflict Research. There are two types of political shocks: forceful or military action which leads to the change of executive authority within the government, and a revolutionary war or violent uprising led by politically organized groups outside current government within that country.

Each of these country-year indicator variables is interacted with the industry technological measure of interest. This interaction variable is the relevant instrument in our context where the independent variables are themselves interaction variables, see Wooldridge (2002) for a theoretical explanation and Ilyina and Samaniego (2011) for an empirical example. The econometric strategy for implementing the instrumental variables procedure using de-meaned variables is described earlier in Section 2.

3.3 Industry outcomes

We measure $Growth_{c,i,t}$ in three ways. First, we use the log change in industry value added, as reported in the INDSTAT3 and INDSTAT4 databases, distributed by UNIDO. Second, we use the log change in gross output. Third, we use the log change in the Laspeyres production index. Having three different growth indices gives the results considerable robustness.

Furthermore, these three measures tell us about different aspects of industry performance. Value added growth tells us about an industry's ability to generate income and contribute to GDP. Gross output growth tells us about production overall, valued at market prices. The production index tells us about production in terms of units rather than market prices.

In addition to industry growth, we investigate growth in a variety of industry indicators to better understand the *channels* whereby contractions might affect the performance of industries with particular technological characteristics. These indicators are: the number of employees, the number of establishments, gross fixed capital formation, and labor productivity. We also create an industry price index, dividing value added by the production index, and examine the growth of this price index.[11] Value added, gross output and gross fixed capital formation are deflated using the CPI of the local currency (from the World Development Indicators). Labor productivity is defined as real value added over the number of employees.

All these variables are reported for 28 manufacturing industries based on the ISIC-revision 2 classification in INDSTAT3. We use only countries for which there are at least 10 years of observations. To avoid the influence of outliers, the 1st and 99th percentiles of $Growth_{c,i,t}$ are eliminated from the sample (the same applies to the other dependent variables considered). We lose some countries as uncertainty data in Baker and Bloom (2013) are not available for the whole globe. This generates a sample of 60 countries from 1970 to 2012, leading to over $40,000$ observations. The panel is unbalanced, and the sample sizes vary across countries and industries as some of the data were not reported by national statistical agencies. Table 1 lists the country sample and the number of observations for each country. Data from 1970 to 2004 are from INDSTAT3, while later data are from the successor dataset INDSTAT4. The United States is not included in the regressions because it is the benchmark economy for measuring industry technological variables.

3.4 Industry Technological Measures

Theory suggests a variety of technological characteristics that could be related to the sensitivity to uncertainty. Below we list the characteristics we consider and describe their measurement. The different technological measures are calculated using U.S. data and are assumed to represent real industry technological characteristics in a (relatively) unregulated and financially frictionless environment. Technological differences among industries are assumed to be persistent across countries, meaning that the rankings of these indices are stable

[11] This procedure is akin to computing the GDP deflator for a particular industry.

Table 1: Country Coverage and Number of Observations

Country	No. of observations	Country	No. of observations
Argentina	961	Kuwait	907
Australia	999	Luxembourg	1,013
Austria	1,013	Mexico	961
Belgium	1,009	Morocco	1,039
Bangladesh	961	Netherlands	1,013
Canada	961	Nigeria	934
China	772	Norway	985
Chile	1,033	New Zealand	1,065
Colombia	1,013	Pakistan	961
Czech Republic	715	Peru	1,065
Denmark	1,013	Philippines	799
Ecuador	1,013	Poland	1,013
Egypt	961	Portugal	1,007
Finland	1,013	Romania	1,039
France	1,013	Russian Federation	499
United Kingdom	1,010	South Africa	1,036
Germany	444	Saudi Arabia	934
Greece	986	Singapore	1,025
Hungary	1,013	Spain	1,011
India	987	Sweden	1,013
Indonesia	1,013	Switzerland	961
Ireland	1,004	Thailand	961
Iran, (Islamic Republic of)	1,013	Tunisia	961
Israel	957	Turkey	961
Italy	1,011	Ukraine	445
Japan	1,013	Venezuela	961
Kenya	1,018	Viet Nam	202
Korea, Republic of	1,039		

across countries, although index values in each country do not necessarily have to be the same.[12] See Rajan and Zingales (1998), Ilyina and Samaniego (2011) and Samaniego and Sun (2015) for related discussions.

As mentioned earlier, we use the growth-theoretic definition of technology as relating to the structure of the production function. We consider the following measures of input intensity and input characteristics, each of which can be related to a source of uncertainty and/or to one of the four mechanisms of uncertainty raised in the theoretical literature. In each case we discuss reasons why the measure might be expected to interact with one or other theory of uncertainty, to motivate their inclusion, but we tie them more closely to particular theories of uncertainty in a later subsection:

- *Labor intensity*: Growth in labor intensive industries might interact more with uncertainty if the volatility or dispersion of Harrod-neutral productivity shocks is a key source of changes in uncertainty. Labor intensity (LAB_i) is measured using the ratio of total wages and salaries over the total value added in the US, using UNIDO data. This represents the overall importance of human capital in production in each industry. In this case we would expect $\beta_2 > 0$ or $\beta_2 < 0$ depending on whether uncertainty encourages or discourages growth, based on the mechanisms discussed earlier. $\beta_2 > 0$ would indicate one of the two expansionary theories is relevant, whereas $\beta_2 < 0$ would indicate a contractionary theory is more relevant.

- *Skilled labor*: While LAB_i measures the overall importance of human capital for production in industry i, it may be that the *type* of human capital matters too. For example, skilled labor may entail higher adjustment costs because of the specificity of human capital, which might lead to greater labor adjustment costs when uncertainty is high due to the accumulation of firm- or task-specific knowledge, in which case we would expect a coefficient $\beta_2 < 0$ for any measure of skill intensity. To examine this possibility we include a human-capital indicator HC_i, measured using the average wage bill (wages divided by number of employees). See Mulligan and Sala-i-Martin (1997).

- *Capital depreciation*: Industries that use capital with high rates of depreciation might fare less well in uncertain times. Real options theory indicates that when investment is irreversible or subject to fixed costs, more uncertainty leads firms to optimally delay investment, and this delay will be more costly if depreciation of the existing capital is

[12] The measures below are drawn from Ilyina and Samaniego (2011) and Samaniego and Sun (2015), and represent averages over the period 1970-2000. Industry measures computed using the Compustat database are median firm values for each industry unless otherwise stated.

rapid. Thus, industries with high depreciation will act before uncertainty is resolved, leading to lower growth and a coefficient of $\beta_2 < 0$. Oi-Hartman-Abel effects would imply opposite, since they predict higher growth among industries where there is more downward flexibility, allowing firms to insure against negative shocks by contracting (high depreciation allows firms to contract simply by not investing, as opposed to actively disinvesting which would require paying fixed costs or incurring irreversibility costs as in Veracierto (2002) for example). Depreciation (DEP_i) is the industry rate of depreciation, computed using the BEA industry-level capital flow tables. It is based on empirical studies of the resale value of capital goods (see Hulten and Wykoff (1981)) and thus reflects all factors that result in the decline in the value of capital goods, including both physical and economic depreciation.

- *Investment specific technical progress*: Investment specific technical change ($ISTC_i$) is viewed by some as an important driver of the cycle e.g. Justiniano et al (2010, 2011), hence it could also be an important source of *uncertainty* if the volatility of ISTC shocks changes over time, having a coefficient $\beta_2 \gtrless 0$ depending on which theory of propagation turns out to be empirically relevant. Also, $ISTC_i$ is a factor of economic depreciation, so it could be related to uncertainty for the same reasons as DEP_i. Investment-specific technical change ($ISTC_i$) is measured using the rate of decline in the quality-adjusted price of capital goods used by each industry, relative to the price of consumption and services, weighting the share of each type of capital using the BEA industry-level capital flow tables. This indicates the extent to which technological obsolescence leads to a decline in the market value of capital goods used in each industry (see for example Greenwood et al (1997)).

- *R&D intensity*: R&D intensive industries could be sensitive to uncertainty for several reasons. R&D is viewed by many as an important driver of the cycle – see Ilyina and Samaniego (2012) for a multisector R&D based growth model. Hence it could also be an important source of *uncertainty* if the volatility of the outcome of R&D changes over time, having a coefficient $\beta_2 \gtrless 0$ depending on which theory of propagation turns out to be empirically relevant. In addition, Corrado et al (2007) find that intangible assets are systematically less durable than tangible assets. Third, R&D investment is up-front and has uncertain payoff, so it may be subject to significant irreversibilities. R&D intensity is also related to finance dependence (Ilyina and Samaniego (2011, 2012), so it could interact with uncertainty if financial sources or channels are important. R&D intensity (RND_i) is measured as R&D expenditures over total capital expenditures, as reported in Compustat – see Ilyina and Samaniego (2011).

- *Asset fixity*: According to Hart and Moore (1994), non-fixed assets are intangible so, as mentioned, they may depreciate more rapidly than fixed assets, as well as being less reversible. Braun and Larrain (2005) argue that asset fixity is a key determinant not of the need for external finance but of the *ability* to raise external funds, so an interaction of fixity with uncertainty could be indicative of financial sources or channels for uncertainty. Asset fixity (FIX_i) is the ratio of fixed assets to total assets, computed using Compustat data following Braun and Larrain (2005).

- *Input specificity*: The specificity of *inputs* makes them more costly to adjust when conditions change, a lack of flexibility which implies greater negative impact of uncertainty according to many of the theoretical mechanisms discussed earlier. One measure of input specificity is the relationship-specificity indicator ($SPEC_i$) developed in Nunn (2007). It measures the extent to which inputs are dependent on relationship-specific investment between the supplier and the buyer. Nunn (2007) measures, for each good, the proportion of inputs that are not sold on an organized exchange nor reference-priced in a trade publication. If inputs are sold on an organized exchange or reference-priced, there must exist a large number of buyers and sellers, indicating this good is not dependent on relationship-specific investments.[13]

  In addition, Cooper et al (1999) and more recently Samaniego (2010) suggest that investment lumpiness (LMP_i) indicates that investment in *physical capital* is subject to significant adjustment costs, either in the form of fixed costs or to irreversibilities. The results of Lanteri (2016) also suggest that capital specificity is an effective adjustment cost. As in Ilyina and Samaniego (2011), lumpiness is defined as the average number of investment spikes per firm during a decade in a given industry, computed using Compustat data. A spike is defined as an annual capital expenditure exceeding 30% of the firm's stock of fixed assets, as in Doms and Dunne (1998).

- *Intermediate intensity*: Industries that use intermediate inputs intensively may also be particularly sensitive to volatility or dispersion in input prices. As a result, an interaction of industry growth with uncertainty in intermediate-intensive industries would indicate the importance of *nominal* volatility as a source of uncertainty shocks. We

[13] Nunn (2007) reports a second measure, the proportion of inputs not being sold on an exchange. This "moderate" measure of relationship specificity is strongly correlated with the "strict" one, but usually performs worse in the regressions than the "strict" measure.

measure intermediate intensity INT_i by dividing gross output by the difference between gross output and value added, as measured in the United States and as reported in INDSTAT3 over the time period of our study.

- *External finance dependence*: Although it is not a strictly technological variable in our sense (finance is not an input as such, but rather a means to acquiring inputs), many studies such as Rajan and Zingales (1998), Braun and Larrain (2005) and Ilyina and Samaniego (2011) find that the industry tendency to draw on external funds is related to growth and the business cycle. As such, any interaction of this variable with uncertainty would indicate the importance of a financial origin to uncertainty or of financial channels, as suggested in Bloom (2009) and Bloom et al (2012) *inter alia*. We measure external finance dependence (EFD_i) as the share of capital expenditures not financed internally, see Rajan and Zingales (1998) and Samaniego and Sun (2015) for details.

Table 2 reports the values of these measures, and Table 3 shows the matrix of correlations among them. Asset fixity and R&D intensity are negatively correlated, as expected. Labor intensity LAB_i and capital depreciation DEP_i are positively correlate. Perhaps surprisingly, $ISTC_i$ and DEP_i are not correlated, since the two are related in theory. On the other hand, DEP_i and LMP_i *are* positively correlated, which is intuitive if we interpret investment lumpiness as evidence of investment irreversibilities or fixed costs of investment, which would lead to some capital depreciation in the event of investment or disinvestment. This fact implies that later findings about DEP_i and LMP_i interacting with uncertainty are not necessarily distinct findings.

Again, central to our identification strategy is the assumption that technological measures X_i are constant across countries and across time. Regarding time variation, Ilyina and Samaniego (2011) show that the rankings of industries according to the above measures computed by decades persist over the period (1970-2000).[14] Regarding country variation, it is important to remember that the assumption is *not* that, for example, LAB_i accurately measures labor intensity in manufacturing industries around the world. The assumption is that this indicates the labor intensity of a typical firm operating in industry i in a relatively undistorted and unconstrained environment. Remember that country- or date-specific factors that affect a given industry will be absorbed by the indicator variables in equation (1). We are interested in how these measures interact with uncertainty. For example LAB_i might not

[14] The exception is $SPEC_i$, for which we lack time series.

Table 2: Industry Technological Measures

Industry	ISIC	EFD	DEP	ISTC	RND	LAB	FIX	LMP	SPEC	HC	INT
Food products	311	-0.039	7.09	3.948	0.073	0.281	0.373	1.195	0.557	1.78	0.658
Beverages	313	-0.048	7.09	3.975	0.039	0.248	0.372	1.29	0.949	2.378	0.549
Tobacco	314	-0.801	5.248	3.975	0.222	0.117	0.189	0.815	0.483	2.648	0.357
Textiles	321	0.029	7.665	3.914	0.144	0.458	0.345	1.232	0.820	1.463	0.586
Apparel	322	0.075	6.437	4.369	0.02	0.447	0.134	1.998	0.975	1.084	0.493
Leather	323	-0.959	9.266	4.008	0.198	0.444	0.135	1.927	0.848	1.439	0.550
Footwear	324	-0.45	8.325	4.056	0.153	0.446	0.16	2.239	0.934	1.156	0.483
Wood products	331	0.052	9.525	3.926	0.032	0.467	0.305	1.72	0.670	1.624	0.596
Furniture, except metal	332	0.015	8.312	4.045	0.155	0.488	0.28	1.381	0.910	1.555	0.484
Paper and products	341	-0.062	8.632	3.25	0.083	0.363	0.472	0.902	0.885	2.406	0.551
Printing and publishing	342	-0.222	9.745	4.41	0.1	0.407	0.261	1.67	0.995	1.969	0.350
Industrial chemicals	351	0.028	9.646	4.595	0.269	0.241	0.381	1.34	0.884	2.921	0.558
Other chemicals	352	1.654	6.888	4.683	1.951	0.218	0.207	2.13	0.946	2.568	0.393
Petroleum refineries	353	-0.055	6.776	3.923	0.057	0.173	0.591	0.763	0.759	3.45	0.833
Misc. pet. and coal products	354	-0.059	6.776	3.996	0.186	0.3	0.372	1.042	0.895	2.395	0.648
Rubber products	355	-0.064	10.072	3.144	0.187	0.423	0.322	1.098	0.923	2.139	0.482
Plastic products	356	0.088	10.072	3.204	0.171	0.402	0.374	1.557	0.985	1.808	0.494
Pottery, china, earthenware	361	-0.107	8.234	4.603	0.503	0.475	0.4	1.292	0.946	1.733	0.311
Glass and products	362	0.289	7.554	4.379	0.115	0.399	0.4	1.755	0.967	2.189	0.409
Other non-met. Min. prod.	369	0.021	8.234	4.754	0.095	0.385	0.48	0.99	0.963	2.072	0.478
Iron and steel	371	-0.004	6.578	3.442	0.066	0.477	0.427	0.951	0.816	2.691	0.578
Non-ferrous metals	372	0.037	5.393	3.431	0.101	0.424	0.364	1.245	0.460	2.373	0.681
Fabricated metal products	381	-0.052	7.043	3.421	0.147	0.455	0.274	1.365	0.945	2.025	0.488
Machinery, except electrical	382	0.542	8.832	5.149	0.933	0.433	0.195	2.694	0.975	2.389	0.479
Machinery, electric	383	0.543	9.381	4.313	0.814	0.407	0.208	2.704	0.960	2.268	0.443
Transport equipment	384	0.041	10.559	3.847	0.316	0.44	0.264	1.614	0.985	2.815	0.598
Prof. & sci. equip.	385	0.942	9.21	4.456	1.194	0.382	0.181	2.79	0.981	2.55	0.344
Other manufactured prod.	390	0.404	10.07	2.996	0.302	0.414	0.186	2.006	0.863	1.64	0.460

Note: EFD_i (external finance dependence), DEP_i (depreciation), $ISTC_i$ (Investment-specific technical change), RND (R&D intensity), LAB_i (labor intensity), FIX_i (fixity), LMP_i (investment lumpiness) , HC_i (human capital intensity) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011); $SPEC_i$ (relationship-specific investment) is taken from Nunn (2007); INT_i (intermediate inputs intensity) from authors calculation. The manufacturing industry classification is 3 digit ISIC rev2.

Table 3: Correlation Matrix of Major Variables

	EFD	DEP	ISTC	RND	LAB	FIX	LMP	SPEC	HC	INT
EFD	1									
DEP	0.0855	1								
ISTC	0.2838	-0.0433	1							
RND	0.7896**	0.0868	0.4605**	1						
LAB	-0.0484	0.3895**	-0.138	-0.1732	1					
FIX	-0.0895	-0.1805	-0.1689	-0.3895**	-0.2217	1				
LMP	0.4980**	0.3931**	0.4077**	0.6058**	0.3065	-0.7232**	1			
SPEC	0.3274	0.5266**	0.2851	0.2729	0.3384	-0.141	0.4247**	1		
HC	0.2391	-0.148	0.0662	0.2394	-0.6013**	0.4503**	-0.2589	-0.1171	1	
INT	-0.2157	-0.2213	-0.3371	-0.4358**	-0.1619	0.5021**	-0.4354**	-0.4150**	0.2667	1

Note: EFD_i (external finance dependence), DEP_i (depreciation), $ISTC_i$ (Investment-specific technical change), RND (R&D intensity), LAB_i (labor intensity), FIX_i (fixity), LMP_i (investment lumpiness), HC_i (human capital intensity) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011); $SPEC_i$ (relationship-specific investment) is taken from Nunn (2007); INT_i (intermediate inputs intensity) is from authors calculation. ** significance level 5%

interact with uncertainty because labor intensity is not a technological feature that interacts with uncertainty. Also, LAB_i might not interact with uncertainty even if labor intensity *is* a technological feature that interacts with uncertainty in theory, if it happens that labor intensity is easily adjusted by firms to deal with uncertainty (e.g. if labor and capital are close substitutes). In either case, deviations from our working assumption will bias our results towards not finding significant interactions.

An alternative of course would be to measure the technological characteristics separately for each country. We do not do this for several reasons. The main reason why we do not wish to use country-specific industry technology measures is that, as discussed, actual labor use in a financially underdeveloped or otherwise distorted economy cannot be viewed as a technological characteristic, since actual input use likely reflects distorted behavior – see Rajan and Zingales (1998) and Ilyina and Samaniego (2011, 2012). Another reason is that the data simply do not exist – except for LAB_i. We computed $LAB_{c,i}$ for each country c and industry i following the procedure described earlier. Then for each country we computed the cross-industry correlation between $LAB_{c,i}$ and LAB_i as measured in the US – our technological measure. We found that this correlation ranged from over 92 percent for the UK to -39 percent in Benin out of the 54 countries for which we were able to compute $LAB_{c,i}$. On the one hand, this indicates some cross-country variation: on the other hand, we found that this correlation was positive and statistically significant at the 5 percent level in 49. In this sense, the US measure LAB_i is not a bad proxy for other countries.

3.5 Controls

In the empirical literature on industry growth it is common to condition on the share of industry i in manufacturing in the previous period, in case there is mean reversion, structural change, or other secular factors of industry growth. We do so as well.

Given the likely correlation between first and second moment shocks, we condition on interactions of the technological variables with the first moment shocks as well. For each measure of uncertainty, the corresponding first moment shock is described earlier.

In addition, Samaniego and Sun (2015) find that technological characteristics may interact with *contractions*, so we condition on interactions of contractions and the technological variables as well, as a non-linear control for business cycle effects. Contractions are defined using a standard peak-trough criterion as implemented by the NBER, see Samaniego and Sun (2015) for details. Our results concerning uncertainty turn out not to be sensitive to the presence of this control.

Finally, an open question in the literature on the macroeconomic impact of uncertainty is whether or not uncertainty stems from the financial sector, or is propagated by the financial sector. We assess this in three ways. First, as mentioned, we use EFD_i as a potential technological interaction variable. If there is an important financial sector role in the macroeconomic impact of uncertainty, we would expect this variable to interact with uncertainty shocks. Second, we do the same with R&D intensity (RND_i), which Ilyina and Samaniego (2011, 2012) find to be a strong correlate and possible technological determinant of EFD_i. Third, we condition on whether or not the interactions of interest are robust to an interaction of technology with a *financial crisis indicator*. We draw on the Systemic Banking Crises Database developed by Laeven and Valencia (2013), which covers the period 1970 to 2011. We define the variable $Crisis_{c,t}$ to equal one if the Database considers country c at date t to be experiencing a banking crisis, and zero otherwise. A year-country pair is determined to be in crisis if there are significant signs of financial distress in the banking system (bank runs, significant bank losses or bank liquidations, and if there is significant policy intervention in response to losses in the banking system. Then, we use $Crisis_{c,t} \times X_i$ as a control for each technological variable X_i, to see whether the results are driven by crises rather than uncertainty and to see whether there are financial channels for uncertainty.

3.6 Hypotheses

To sum up, we re-state the different theories of uncertainty in the literature, linking them to particular technological interactions our empirical strategy aims to identify:

3.6.1 Sources of uncertainty

- In general, if uncertainty stems from shocks that particularly affect a particular type of industry or a particular input, we would expect to see that type of industry or industries that use that type of input intensively to react most in the face of uncertainty. For example, uncertainty deriving from the volatility or dispersion of Harrod-neutral productivity shocks (the source of uncertainty in the model of Bloom et al (2012)) would be expected to affect labor-intensive industries the most (LAB_i). Uncertainty deriving from the process of growth through technical progress using new techniques should impact R&D-intensive industries more than others (RND_i). If uncertainty stems from ISTC, a high value of $ISTC_i$ would be related to greater sensitivity instead.

- If price uncertainty is important, we would expect to see intermediate-intensive firms react the most to uncertainty (INT_i). In addition, whatever industries react the most to uncertainty, we would expect to see an impact of uncertainty on the industry *price indices* we constructed. Specificity of inputs ($SPEC_i$), or input intensity (INT_i), might interact with uncertainty to the extent that uncertainty is related to volatility of input prices or of gross output productivity, or if inputs rather than capital or labor are subject to important adjustment costs.

- If financial uncertainty is key, then we would expect to see a disproportionate impact of uncertainty on industries with high external finance dependence (EFD_i) or R&D intensity (RND_i). We would also expect whatever industries are most sensitive to uncertainty to be sensitive also to financial crises ($Crisis_{c,t}$).

3.6.2 Propagation mechanisms of uncertainty

- If real options theory is an important propagation mechanism of uncertainty, this might be observed most sharply in industries where capital depreciation is rapid (DEP_i) or where input adjustment costs are high, since this increases the cost of waiting for uncertainty to be resolved (LMP_i, $SPEC_i$). This might also be expected to particularly impact high-human capital industries (HC_i), because unskilled labor is easier to adjust than skilled labor, which may entail more firm- or task-specific knowledge than unskilled labor. We would also expect to see declining labor productivity in these industries as firms would be acting before uncertainty is fully resolved, leading to a higher likelihood of unproductive investments.[15]

- If risk aversion is an important propagation mechanism of uncertainty, since this works through financial channels such as increases in the cost of external finance, we would expect to see a disproportionate *negative* impact of uncertainty on industries with high external finance dependence (EFD_i) or R&D intensity (RND_i). Again, we might also expect whatever industries are most sensitive to uncertainty to be sensitive also to financial crises ($Crisis_{c,t}$).

- If growth options theory is an important propagation mechanism of uncertainty, we would expect industries that are linked to the process of economic growth (LAB_i, $ISTC_i$ and/or RND_i) to display a *positive* interaction with uncertainty. In addition, we might expect high growth in the more flexible industries, or low growth in the more inflexible industries (e.g. high LMP_i, $SPEC_i$ or HC_i), depending on which type of inflexibility is more important – for capital, intermediates, or labor. Since this theory relies on the ability to rapidly revert to an old project if new projects do not work, however, we might expect a negative coefficient on DEP_i, since this would imply that the capital used in the old project would depreciate rapidly while the new project is explored unless it is possible to costlessly move resource between projects or maintain the old project costlessly. In addition, since this theory implies that firms act as though they were risk-loving, we might expect to see this mostly in the stock-market based measures of uncertainty.

- If Oi-Hartman-Abel effects constitute an important propagation mechanism of uncertainty, we would again expect high growth in the more flexible industries, or low growth in the more inflexible industries (e.g. high LMP_i, $SPEC_i$ or HC_i). Since according to this theory these industries display low growth because they cannot expand to take advantage of any positive productivity shocks that might appear, they should display disproportionately slow labor productivity growth and also slow growth in capital expenditures and employment. However, because according to this theory the key mechanism for uncertainty to affect industry growth is the ability to contract rapidly and costlessly in the event of *negative* shocks, this would suggest that DEP_i

[15] This may not apply to high-HC_i industries: if unskilled labor is easy to fire (or adjust), then labor productivity may increase when the more productive skilled labor is kept.

should carry a *positive* coefficient, since rapid depreciation allows firms to contract without incurring fixed investment costs or the costs of irreversibilities. Again, since this theory implies that firms act as though they were risk-loving, we might expect to see this mostly in the stock-market based measures of uncertainty.

4 Findings

4.1 Empirical results

We first estimate the basic regression equation (1) using the three measures of industry growth as the dependent variable and inserting the interaction terms of uncertainty with the technological variables one by one. We begin by spelling out the results and turn to a full analysis thereof later.

First, there are various technological interactions with statistical significance: see Table 4. However, almost all of them occur for one measure of uncertainty: *bond volatility.* A few occur for exchange rate volatility, but none for the other measures of uncertainty. Thus, the key measure of uncertainty leading to dispersion in industry growth appears to be *systemic volatility.*

Second, there are several statistically significant interactions of technology with systemic uncertainty, the only technological variables that interact *robustly* with uncertainty – in the sense that there is a significant interaction regardless of the measure of industry growth – are depreciation DEP_i and investment lumpiness LMP_i. Other technological interactions are not robust either in that they have inconsistent sign or inconsistent statistical significance. As discussed later, this finding is robust to a variety of controls and robustness checks. We conclude that the key interactions of interest are between uncertainty and these two technological variables, DEP_i and LMP_i.

We learn more about the interaction of capital depreciation and lumpiness with uncertainty by examining dependent variables other than industry growth. These include the growth of capital formation, employment, the number of establishments, labor productivity and prices. See Table 5.

We find that high-depreciation and high-lumpiness industries experience slower labor productivity growth in uncertain times. This is consistent with the hypothesis that fixed costs of investment lead these firms not to replace depreciating capital while they wait for uncertainty to be resolved. It is also consistent with the notion that firms are losing labor productivity because, pending the resolution of uncertainty, they are deferring investments in

Table 4: Basic Results

This table represents results from the following regression:

$$Growth_{c,i,t} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \beta_1(LevelShock_{c,t} \times X_i) + \beta_2(UncertaintyShock_{c,t} \times X_i) + \beta_3 Controls_{i,c,t} + \epsilon_{c,i,t}$$

We only report β_2. Each cell represents one regression. The dependent variable is industry value added growth rate, output index growth rate and gross output growth rate. Independent variables are the following: EFD_i(external finance dependence), DEP_i(depreciation), $ISTC_i$(Investment-specific technical change), RND (R&D intensity), LAB_i(labor intensity), FIX_i(fixity), LMP_i(investment lumpiness) , HC_i(human capital intensity) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011); $SPEC_i$(relationship-specific investment) is taken from Nunn (2007); INT_i(intermediate inputs intensity) is from authors calculation. The uncertainty measures are stock market returns, cross section, bond yield and exchange rate volatility from Bloom et al (2012). Standard errors in parentheses, *** p<0.01, ** p<0.05.

UNCERTAINTY	Value Added Growth Regression				Output Index Growth Regression				Output Growth Regression			
	Stock	Cross	Bond	Xrate	Stock	Cross	Bond	Xrate	Stock	Cross	Bond	Xrate
EFD	-14.30	12.64	-0.256	-0.170	0.0612	0.160	-0.0134	-0.0798**	-6.854	1.888	0.0201	0.156
	(13.58)	(19.04)	(0.144)	(0.550)	(0.380)	(0.173)	(0.00798)	(0.0400)	(5.822)	(8.160)	(0.0420)	(0.401)
DEP	-9.009	11.59	-0.284***	0.274	-0.0887	-0.0323	-0.00679***	-0.00680	-1.225	-1.384	-0.139**	0.0415
	(14.79)	(20.19)	(0.0576)	(0.626)	(0.104)	(0.0395)	(0.00258)	(0.0183)	(9.136)	(1.963)	(0.0540)	(0.438)
ISTC	-5.580	-1.662	-0.0365	1.210**	-0.243	0.0257	-0.0181***	0.0146	-11.10	-5.206	-0.178	1.627
	(12.69)	(8.067)	(0.0993)	(0.569)	(0.226)	(0.114)	(0.00568)	(0.0379)	(17.03)	(5.862)	(0.102)	(1.227)
RND	-11.77	12.29	-0.188	0.176	-0.194	0.147	-0.0243**	-0.0668	-2.884	-0.181	-0.145**	0.567
	(19.87)	(39.40)	(0.127)	(0.841)	(0.318)	(0.192)	(0.00989)	(0.0449)	(6.784)	(5.970)	(0.0724)	(0.380)
HC	23.45	-36.17	0.603***	-2.283	-0.311	-0.0670	-0.00688	-0.0614	6.435	-2.708	0.187	-0.945
	(18.94)	(38.71)	(0.230)	(1.401)	(0.547)	(0.132)	(0.00753)	(0.0343)	(6.984)	(5.237)	(0.105)	(0.574)
LAB	-190.7	219.0	-3.709***	7.160	-1.269	-0.667	-0.0167	-0.343**	-75.25	-6.563	-0.788	2.886
	(153.4)	(191.9)	(1.257)	(7.397)	(1.084)	(0.548)	(0.0329)	(0.167)	(101.3)	(62.35)	(0.554)	(3.555)
LMP	-33.25	34.90	-0.676***	1.419	-0.392	0.0659	-0.0233***	-0.0607	-13.12	-2.801	-0.297***	1.373**
	(32.57)	(42.65)	(0.189)	(1.369)	(0.344)	(0.122)	(0.00604)	(0.0416)	(11.34)	(5.228)	(0.0765)	(0.668)
FIX	69.70	-138.6	2.163	-4.183	1.232	-0.282	0.108***	0.159	30.36	16.14	1.263**	-4.550
	(79.68)	(224.0)	(1.162)	(5.301)	(2.180)	(0.552)	(0.0381)	(0.230)	(40.50)	(32.38)	(0.532)	(2.568)
SPEC	-29.42	45.80	-1.464***	0.924	-1.366	-0.108	-0.0553***	-0.0616	-28.88	-14.17	-0.929	3.247**
	(51.22)	(39.80)	(0.428)	(3.311)	(0.710)	(0.316)	(0.0185)	(0.140)	(25.87)	(21.20)	(0.480)	(1.646)
INT	171.6	-256.6	3.780**	-12.45	0.325	-0.291	0.0328	0.0939	62.20	16.22	1.887**	-4.518
	(233.3)	(402.9)	(1.481)	(11.52)	(1.416)	(0.569)	(0.0366)	(0.227)	(89.31)	(47.79)	(0.921)	(4.047)
Observations	20,168	12,625	16,149	29,926	18,519	11,386	15,115	27,511	20,166	12,630	16,152	29,960

growth opportunities. Thus, either firms in these industries are forced to act hastily because of the cost of waiting (as in the contractionary theories of uncertainty) or they are unable to take advantage of positive opportunities that come along (as in the expansionary theories).

We also find that high-lumpiness industries also experience slower employment growth. Where lumpiness (and fixed investment costs) is low, firms can invest and maintain capacity while waiting for uncertainty to be resolved. On the other hand, where lumpiness (and fixed investment costs) are high, it may be very costly to maintain capacity while waiting so that firms' capital stock shrinks and, optimally, so does the labor force.

Interestingly, both types of industries experience *higher* growth rates in the number of establishments, compared to other industries. This implies either disproportionately high entry or disproportionately low exit in these industries in times of uncertainty. It is not obvious what implications this finding has for most of the theories of uncertainty without developing models of how each of them is linked to the process of entry and exit. However, there is one exception. *Risk aversion theory* hinges on uncertainty raising the costs of external funds, which would likely suppress activity by both entrants and incumbents, suppressing entry and increasing exit and leading to a *decrease* in the number of establishments in the most affected industry. This is inconsistent with our findings.

Finally, we do not notice any differential interaction with price growth, nor capital growth (specifically, growth in gross fixed capital formation). The former suggests that price uncertainty is not important for our findings. The latter suggests that, even though the costs of capital adjustment or of maintaining the capital stock differ across industries, and even though these variables DEP_i and LMP_i interact with uncertainty, interestingly gross investment behavior is not necessarily very different.

4.2 Analysis

We now relate our findings explicitly to the matrix of 12 broad theories of uncertainty mentioned earlier in Section 2.

4.2.1 Sources of shocks

Nominal sources: First of all, we do not find evidence of any relationship between uncertainty and nominal sources. The only nominal uncertainty measure – exchange rate volatility – is not robustly related to any technological measure. Intermediate intensity INT_i does not robustly interact with uncertainty. Most tellingly, for the industry characteristics that do interact with uncertainty, there is no disproportionate movement in price indices.

Table 5: Mechanisms

This table represents results from the following regression:

$$Growth_{c,i,t} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \beta_1(LevelShock_{c,t} \times X_i) + \beta_2(UncertaintyShock_{c,t} \times X_i) + \beta_3 Controls_{i,c,t} + \epsilon_{c,i,t}$$

We only report β_2. Each cell represents one regression. The dependent variable $Growth_{c,i,t}$ is industry capital formation, employment, establishment, labor productivity and price growth rate. Independent variables are the following: DEP_i (depreciation) and LMP_i (investment lumpiness) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011). Bond uncertainty measure is from Bloom et al (2012). Standard errors in parentheses, *** p<0.01, ** p<0.05.

Bond Uncertainty	Capital formation growth rate regression	employment growth rate regression	establishment growth regression	Labor productivity growth rate regression	Price growth rate regression
DEP	-0.237	-0.00621	0.190**	-17.58***	0.0161
	(0.125)	(0.00729)	(0.0802)	(3.428)	(0.0306)
LMP	-0.155	-0.0556**	0.484***	-44.91***	-0.0659
	(0.446)	(0.0274)	(0.186)	(8.915)	(0.0563)
Observations	12,532	16,236	9,804	16,006	14,327

Financial sources: We do not find any relationship between uncertainty and finance. We do not find that external finance dependence (EFD_i) interacts with uncertainty shocks. In addition, Ilyina and Samaniego (2011) argue that the deep technological characteristic underlying external finance dependence is in fact R&D intensity: we do not find evidence of an interaction between uncertainty and RND_i either. The absence of evidence linking uncertainty with financial dependence is consistent with the findings of Caldara et al (2016), who find that while uncertainty may sometimes have an impact on financial markets they are not the main source thereof.

To further explore this question, we do two things. First, we examine whether our uncertainty measures are correlated with the financial crisis indicator $Crisis_{c,t}$. We find that, in fact, the correlation between $Crisis_{c,t}$ and uncertainty is quite high. The correlations range between 9.29 percent for bond market uncertainty and 24.0 percent for stock market volatility and are very highly statistically significant (for example, the computation of the correlation of $Crisis_{c,t}$ with bond market volatility uses $35,804$ observations). The relationship remains highly statistically significant even when we condition on country fixed effects. This suggests that there could be a finance-uncertainty link. Then, we introduce into our specification an additional control in the form of an interaction variable of the technological variables with

Table 6: Control Banking Crisis

This table represents results from the following regression:

$$Growth_{c,i,t}= \delta_{i,c}+\delta_{i,t}+\delta_{c,t}+\beta_1(LevelShock_{c,t}\times X_i) + \beta_2(UncertaintyShock_{c,t}\times X_i) + \beta_C(Crisis_{c,t} \times X_i) +$$

We only report $\beta_2$and β_C. Each cell represents one regression. The dependent variable is value added, output index and output growth rate respectively. Independent variables are the following: DEP_i (depreciation) and LMP_i (investment lumpiness) are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011). Bond uncertainty measure is from Bloom et al (2012). Banking crisis data is from Laeven et al. (2013). Standard errors in parentheses, *** p<0.01, ** p<0.05.

Output growth measure	INTERACTION	DEP	LMP
Valua added growth	Crisis×X	-0.0829	0.0256
		(0.0981)	(0.273)
	Bond Uncertainty×X	-0.295***	-0.702***
		(0.0550)	(0.208)
Output index growth	Crisis×X	0.00234	0.00147
		(0.00381)	(0.0105)
	Bond Uncertainty×X	-0.00668***	-0.0234***
		(0.00254)	(0.00727)
Output growth	Crisis×X	0.0220	0.285
		(0.0717)	(0.242)
	Bond Uncertainty×X	-0.142**	-0.303***
		(0.0610)	(0.0904)

Standard errors in parentheses, *** p<0.01, ** p<0.05.

the financial crisis indicator $Crisis_{c,t}$. The specification then becomes:

$$Growth_{c,i,t} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \beta_1(LevelShock_{c,t} \times X_i) + \beta_2(UncertaintyShock_{c,t} \times X_i) \\ + \beta_C(Crisis_{c,t} \times X_i) + \beta_3 Controls_{i,c,t} + \epsilon_{c,i,t}$$

We find that, first of all, the impact on industry growth of the interaction of LMP_i and of DEP_i with systemic uncertainty is robust to the inclusion of this control variable, indeed it remains statistically significant for all three measures of industry growth. Furthermore, the interactions of $Crisis_{c,t}$ with LMP_i and with DEP_i are not significant. Thus, our approach to identifying the macroeconomic impact of uncertainty does *not* uncover any evidence of a significant financial channel underlying our findings. See Table 6.

Real sources: We also do not find any consistent link between uncertainty and any of the technological variables typically associated with real shocks in growth-based business cycle models *à la* Kydland and Prescott (1982): LAB_i, $ISTC_i$ and RND_i. Greenwood et al (1988) argue for a model of the business cycle where shocks to the marginal efficiency of investment (i.e. ISTC) are important, but that the key propagation mechanism is the utilization rate (which increases depreciation). If high-depreciation industries are also industries where depreciation is most sensitive to utilization (which makes sense if the depreciation rate of unutilized capital is close to zero) then utilization will be highly sensitive to uncertainty in these industries. Assuming upward growth is bounded by 100 percent utilization, and that utilization rates in general are fairly high, this would suggest that industries with high depreciation are more likely to experience disproportionately low growth because they can contract easily if shocks are bad, but cannot expand much when shocks are good. If lumpiness is an indicator of fixed costs, again utilization rather than changes in investment becomes a key margin of adjustment to shocks, and therefore to uncertainty. However, in this case we would expect to see disproportionately low investment in these industries in uncertain times (since the inability to invest when shocks turn out to be good is the key mechanism here), which is something we do not see.

We conclude that any consistent source of real shocks is not obviously related to the growth process. An example would be policy uncertainty, something that is explored in Baker et al (2016) and Stokey (2016). Alternatively, another possibility is that there is no consistent source of uncertainty, rather uncertainty may come from any direction.

4.2.2 Propagation mechanisms

First we turn to the contractionary mechanisms, risk aversion and real options. Then we turn to the expansionary mechanisms, growth options and Oi-Hartman-Abel effects.

Risk aversion: Risk aversion theory leads uncertainty to affect industry dynamics mainly through financial channels, particularly through the cost of borrowing. This is consistent with the fact that bond market uncertainty is the main measure of uncertainty that interacts with industry growth. However, we would also expect growth in EFD_i- or RND_i-intensive industries to be especially slow during uncertainty shocks, since these industries depend the most on external financing. Alternatively, we would expect crises and uncertainty shocks to display some similarities in terms of their technological interactions. As discussed above, we do not find any of these effects. Finally, risk aversion theory works through higher external financing costs in uncertain times, which should hurt both entrants and incumbents, reducing entry and increasing exit. The fact that the industries that grow slowest in uncertain times see an *increase* in the number of enterprises is inconsistent with this theory.

Real options: Real options theory, on the other hand, is consistent with the results. DEP_i and LMP_i are factors that would make it costly to wait for the resolution of uncertainty, leading to hasty decisions in the form of either premature investment in new projects or premature exit. In the theory of real options, when a firm faces an imperfectly reversible growth opportunity, an important consequence of any uncertainty regarding the payoff from the opportunity is that waiting for the uncertainty is resolved becomes a valuable option. Pursuing the growth opportunity is equivalent to exercising the option and giving up the possibility of waiting for more information – a possibility which is more valuable when there is greater uncertainty, and which would lead to the more efficient adoption (and rejection) of growth opportunities.

Consider the impact of depreciation on the value of the option to pursue a growth opportunity. When capital depreciates rapidly, not exercising the option means a rapid decline in the capital stock (or a greater cost to replacing depreciated capital), and hence it is more costly to wait in such industries. When uncertainty is high, industries that can wait costlessly will do so, whereas those where waiting is costly (e.g. depreciation is rapid, or there are fixed costs to replacing depreciated capital) will not be able to wait as long before they incur the up-front costs of investment, and will do so before uncertainty has been fully resolved, meaning sometimes they will pursue projects that are not profitable, slowing growth.

Now consider the impact of investment lumpiness, generally interpreted to indicate a fixed cost of investment – as in Cooper et al (1999). When capital is not costly to adjust, the firm holding the option may seamlessly top up its current capital to maintain the profitability of the old project while it waits for uncertainty to be resolved. On the other hand, where fixed costs of investment are large, uncertainty becomes costly as the firm does not invest and its capital declines (unless it pays the fixed cost). Again, the firm may not be able to wait for uncertainty to be resolved, and may adopt projects that are found later not to be profitable, slowing growth. This may also result in firings – and hence lower employment growth – because if capital and labor are at all substitutable an industry where fixed costs of investment or investment irreversibilities are high may optimally prefer to shrink in response to lower productivity by firing rather than disinvesting. This employment effect may not be visible in high-DEP_i industries because disinvestment there is easier.

Growth options: According to this theory, if reversion to an old project is easy, uncertainty creates larger profit opportunities that are insured by the possibility of reverting to the prior project in case downside risk materializes. In this case, we would expect industries where growth opportunities are abundant to interact (positively) with uncertainty. Growth theory emphasizes neutral technical progress, investment specific technical progress, R&D and human capital accumulation as key factors of economic growth. However, none of these turn out to interact robustly with uncertainty.

In addition, the finding that the number of establishments goes up in the industries with negative growth interactions goes against this theory. In conjunction with our interaction findings, this theory would imply that high-DEP_i and high-LMP_i industries have a harder time taking advantage of growth opportunities when there is uncertainty. In this case, there should be an increase in exit compared to other industries where incumbents can take advantage of growth opportunities, and thus a *decrease* in the number of firms unless there is a disproportionately large number of entrants. This seems unlikely since for entrants reverting to the "prior project" takes the form of exit. Since many incumbents do survive this implies that the benefit from exiting is not as large as the benefit from reverting to old projects: it is incumbents, not entrants, who are better positioned to take advantage of growth opportunities.

Finally since this theory hinges on firms becoming risk-loving we would expect interactions with the stock-market based measure of uncertainty, which concerns riskier assets. We do not find any such interactions.

Oi-Hartman-Abel effects: These effects emphasize the possibility of rapid expansion and contraction depending on how uncertainty is resolved, which provides implicit insurance to firms against negative shocks. This insurance should not be readily available to firms where *contraction is costly*. This means firms where fixed costs are high or investment irreversibilities are significant (e.g. LMP_i is high), or where depreciation (DEP_i) is low – because high depreciation allows the firm to contract without having to disinvest. This is consistent with the negative interaction of uncertainty with LMP_i, but not with the negative interaction with DEP_i: a positive coefficient would be expected. In addition, one would expect that gross capital formation would be disproportionately low in high-LMP_i industries, since this is the key mechanism of Oi-Hartman-Abel effects: we observe no such phenomenon.

Also, since this theory hinges on firms becoming risk-loving we would expect interactions with the stock-market based measure of uncertainty, which concerns riskier assets. We do not find any such interactions.

finally, since this mechanism revolves around the timing - rather than the volume - of investment, it does not have clear implications for whether or not investment would be expected to be disproportionately high or low, so it is consistent with the absence of an interaction of DEP_i and LMP_i with capital expenditures growth.

4.3 A simple model

To conclude, we find that our results are mainly consistent with the real options theory of uncertainty propagation. We describe below a simple model of how we see real options theory being consistent with our findings. The purpose is to clarify in a simple framework some key assumptions that might be useful in further research for confirming our interpretations or more generally for sorting among theories. The key assumptions are that uncertainty provides opportunities for the better, as well as for the worse, and that (as assumed by real options theory) full costless reversion to a prior project is not possible after investing in a new project. Then, depreciation and lumpiness are essentially proxies for the *holding costs* of the old project.

Consider an environment with three stages $t \in \{0, 1, 2\}$: an initial stage, a stage of uncertainty and a stage where uncertainty is resolved. We consider these three stages to take place over the course of a year, the period length in our data. In this environment there is a firm that discounts the future with factor $\beta \in (0, 1]$, which has a current project that yields π_{old} in stage 0, a benchmark period. In stage $t > 0$ it yields $\pi_{old}(1 - \delta)^t$. This reflects two possibilities. One is that capital in the project depreciates and is costly to replace. Another is that capital investment is subject to fixed costs, so the project declines in size because capital depreciates and is replaced rarely and in lumps. Thus, the parameter δ captures aspects of depreciation and also of investment lumpiness.

There is also an uncertain investment option available to the firm, which pays $\pi_{new} + \varepsilon$. The random variable $\varepsilon \in \{-\upsilon, \upsilon\}$, each with probability 0.5. The firm can switch to the new project, but only by abandoning the old project, in which case it's old capital invested in the old project becomes worthless. For example, retooling a factory to produce a new model of a product requires the removal of the old configuration and machinery, and may even require changes to the work force or the management structure if the required knowledge is different. Thus there is investment irreversibility. For simplicity, we assume it is complete i.e. adopting the new growth opportunity entails the complete obsolescence of the old one.

If the firm adopts the project in stage 1, it does so without observing the value of ε. If it adopts the project in stage 2, however, it does so under complete information. Notice that there are several interpretations of this setup. ε could be an idiosyncratic variable that is temporarily subject to uncertainty. On the other hand, ε could also be an aggregate variable that is revealed when agents start to act on it in stage 1, so agents who wait until stage 2 can free-ride on the information generated in period 1.

Finally, suppose that $\pi_{new} > \pi_{old}$, and that $\pi_{old} > \pi_{new} - \upsilon$. In other words, the expected profitability of the new project exceeds that of the old: however, it is inferior in certain states of the world. Thus, under complete information, the growth opportunity would only be adopted when it is superior to the old project, not otherwise.

Now we examine the firm's payoffs. In stage 0 the firm simply earns π_{old}. In stage 1, if they do not switch projects they get $\pi_{old}(1-\delta)$. If they do switch however they earn $\pi_{new}+\varepsilon$. Since uncertainty is symmetrical, in expectation they get π_{new}.

In stage 2 the firm has full information. If they did not adopt the new project in stage 1, they will do so in stage 2 only if it is profitable to do so, thus they earn either $\pi_{new}+\upsilon$ or $\pi_{old}(1-\delta)^2$ with probability half. On the other hand, if they did adopt the new project in stage 1, they would earn in expectation $\pi_{new}(1-\delta_{new})$, where δ_{new} is the depreciation rate associated with the new project.

The firm's expected payoff is then:

$$\pi_{old}+\max\left\{\beta\pi_{new}+\beta^2\pi_{new}(1-\delta_{new}),\beta\pi_{old}(1-\delta)+\frac{1}{2}\beta^2\pi_{old}(1-\delta)^2+\frac{1}{2}\beta^2(\pi_{new}+\upsilon)\right\}$$

The firm updates in stage 1 before uncertainty is resolved iff

$$\pi_{new}+\beta\pi_{new}(1-\delta_{new})>\pi_{old}(1-\delta)+\frac{1}{2}\beta\pi_{old}(1-\delta)^2+\frac{1}{2}\beta(\pi_{new}+\upsilon).$$

Clearly a higher value of υ – greater uncertainty – does not change the expected value of the new project at all. At the same time, greater uncertainty raises the value of waiting relative to the value of not waiting.

Notice also that the left hand side does not depend on δ, whereas the right hand side declines with δ. Thus the firm is more likely to update early when δ is higher. This means that it will sometimes adopt growth opportunities under uncertainty when under complete information it would have been optimal to let them pass, thus having lower growth on average.

This simple environment clarifies some of the assumptions required to explain our findings using real options theory. The old project and the new project must have different features. This is reflected in the idea that the capital cannot be fully transferred between projects, but also in that the values of δ for the two projects are not perfectly correlated. Then, the reason lumpiness and depreciation slow growth is because these two variables mainly reflect the cost of maintaining current operations, as opposed to the cost of switching to a new operation.

It is worth noting that one particular option that firms might face in times of greater uncertainty – the option to *cease operations* – very much looks like this. Whatever the firm (or owners or managers of the firm) might do if they shut down the firm is likely quite unconnected with whatever is happening at the firm itself right now. If uncertainty raises the possibility of exit, and maintaining operations is costly, because DEP or LMP are high, the firm may shut down even when the uncertainty about whether or not this is optimal has been resolved, leading to low growth in the industry.

5 Conclusion

We provide an anatomy of how uncertainty affects different parts of the macroeconomy, in order to understand the sources and/or impact of uncertainty on the macroeconomy. Our project allows us to understand the key mechanisms whereby uncertainty affects the macroeconomy, and thus deepening our understanding of the role of uncertainty in the macroeconomy and of its role as a cause of the business cycle in particular. We find that industries where the holding cost of current investments is high suffer more in the face of uncertainty, consistent with them being forced to act before uncertainty is resolved – either taking on new projects before their worth has been proven, or simply shutting down operations. In this way, our finding is consistent with the theory of real options. While we cannot identify a consistent source of macroeconomic uncertainty, we do find that financial considerations are not in general important for our results. This is consistent with Caldara et al (2016) but in contrast to Arellano et al (2012) and Gilchrist et al (2014).

Our research is the first to provide a detailed anatomy of the impact of uncertainty at the industry level, using the technology of production as an organizing principle. Our research exercise is also comprehensive given the large sample of countries, different measures of technology, industry growth and uncertainty. Of course, like all studies, ours has limitations that should be kept in mind in interpreting results and in thinking of future work. One caveat is that we limit ourselves to manufacturing sector data, due to the availability of the data used to construct the technological measures, as well as the availability of industry growth data in non-manufacturing industries for a large panel of countries. At the same time, since our measures are related to the technology of production, not the nature of the output, there is no particular reason why these results should not extend to other sectors.

We underline that we measure "uncertainty" in terms of observed volatility, as in Bloom (2009) and Baker and Bloom (2013) inter alia. Jurado et al (2015) use a different approach to the measurement of uncertainty based on the notion of unforecastability. It would be interesting to extend our study using this alternative approach: however it is challenging to implement since it would require not only a very large set of economically important time series for each country but also a set of time series that spans a similar information set in each case. Nonetheless, since the two interpretations of uncertainty as volatility vs. unforecastability are not orthogonal, and since we find that the uncertainty measures based on the two interpretations/measurement approaches are highly correlated for the US, our results should apply to both. Although our approach is different, we share the same objective as Jurado et al (2015): to develop criteria for narrowing down the empirically relevant approaches to modeling the macroeconomic impact of uncertainty. We find that systemic uncertainty, real options and the costs of delaying investment in new projects are important elements of any such approach.

6 References

References

[1] Abel, Andrew B. 1983. Optimal Investment Under Uncertainty. American Economic Review 73(1), 228 –33.

[2] Anderson, James E., van Wincoop, Eric, 2004. Trade costs. Journal of Economic Literature 42 (3), 691–751.

[3] Arellano, Cristina, Yan Bai and Patrick Kehoe. 2012. Financial Markets and Fluctuations in Volatility. Federal Reserve Bank of Minneapolis Research Department Staff Report 466.

[4] Baker, Scott R. and Nicholas Bloom. 2013. Does Uncertainty Reduce Growth? Using Disasters as Natural Experiments. NBER Working Paper No. 19475.

[5] Baker, Scott R., Nicholas Bloom and Steve Davis. 2016. Measuring Economic Policy Uncertainty. Forthcoming Quarterly Journal of Economics.

[6] Barlevy, Gadi. 2007. On the Cyclicality of Research and Development. American Economic Review 97(4), p1131-1164.

[7] Bernanke, Ben S. 1983. Irreversibility, Uncertainty, and Cyclical Investment. Quarterly Journal of Economics 98(1), 85-106.

[8] Bertrand, Marianne, Esther Duflo and Sendhil Mullainathan. 2004. How Much Should We Trust Differences-In-Differences Estimates? Quarterly Journal of Economics 119 (1), 249-275.

[9] Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten and Stephen J. Terry. 2012. Really Uncertain Business Cycles. NBER Working Paper No. 18245.

[10] Bloom, Nicholas. 2014. Fluctuations in Uncertainty. Journal of Economic Perspectives 28(2), 153-176.

[11] Braun, Matias, and Borja Larrain, 2005, Finance and the Business Cycle: International, Inter-Industry Evidence, Journal of Finance 60(3), 1097-1128.

[12] Caldara, Dario, Cristina Fuentes-Albero, Simon Gilchrist and Egon Zakrajšek. 2016. The macroeconomic impact of financial and uncertainty shocks. Forthcoming, European Economic Review.

[13] Calvo, Guillermo A. 1983. Staggered Prices in a Utility-Maximizing Framework. Journal of Monetary Economics 12, 383-98.

[14] Campbell, Jeffrey R. 1998. Entry, Exit, Embodied Technology, and Business Cycles. Review of Economic Dynamics 1, 371-408.

[15] Cobb, Charles W., and Paul H. Douglas, 1928, A theory of production, American Economic Review 18(1), 139-165.

[16] Cooley, Thomas F. and Edward C. Prescott. 1995. Economic Growth and Business Cycles. In *Frontiers of Business Cycle Research*. Thomas F. Cooley (Ed.). Princeton University Press, New Jersey.

[17] Cooper, Russell, John Haltiwanger and Laura Power. 1999. Machine Replacement and the Business Cycle: Lumps and Bumps. American Economic Review 89(4), 921-946.

[18] Corrado, Carol, Charles Hulten and Daniel Sichel. 2007. "Intangible Capital and Economic Growth." Research Technology Management.

[19] Dixit, Avinash K. and Robert S. Pindyck. 1994. Investment under Uncertainty. Princeton University Press, New Jersey.

[20] Doms, Mark E. and Timothy Dunne, 1998, Capital Adjustment Patterns in Manufacturing Plants, Review of Economic Dynamics 2, 409-429.

[21] Gilchrist, Simon, Jae W. Sim, Egon Zakrajšek. 2014. Uncertainty, Financial Frictions, and Investment Dynamics. NBER Working Paper No. 20038.

[22] Greenwood, Jeremy, Zvi Hercowitz and Gregory W. Huffman. 1988. Investment, Capacity Utilization, and the Real Business Cycle. American Economic Review 78(3), 402-417.

[23] Greenwood, Jeremy, Hercowitz, Zvi and Krusell, Per, 1997. Long-Run Implications of Investment-Specific Technological Change, American Economic Review 87(3), 342-62.

[24] Greenwood, Jeremy, Zvi Hercowitz and Per Krusell. 2000. The Role of Investment-Specific Technological Change in the Business Cycle. European Economic Review 44(1), 91-115.

[25] Hart, Oliver, and John Moore, 1994, A theory of debt based on the inalienability of human capital, Quarterly Journal of Economics 109(4), 841-879.

[26] Hartman, Richard. 1972. The Effects of Price and Cost Uncertainty on Investment. Journal of Economic Theory 5(2), 258–66.

[27] Hérbert, Benjamin. 2016. Moral Hazard and the Optimality of Debt. Mimeo: Stanford University.

[28] Herrendorf, Berthold, Rogerson, Richard, Valentinyi, Akos, 2013b. Two perspectives on preferences and structural transformation. American Economic Review 103 (7), 2752–2789.

[29] Hulten, Charles R., and Frank C. Wykoff. 1981. "The Measurement of Economic Depreciation." In Depreciation, Inflation, and the Taxation of Income from Capital, edited by Charles R. Hulten, 81–125. Washington, DC: The Urban Institute Press.

[30] Ilyina, Anna, and Roberto Samaniego. 2011. Technology and Financial Development, Journal of Money, Credit and Banking 43(5), 899-921.

[31] Ilyina, Anna and Samaniego, Roberto M. 2012. Structural Change and Financing Constraints. Journal of Monetary Economics 59(2), 166-179.

[32] Jensen, Michael C. and William H. Meckling. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics 3(4), 305-360.

[33] Jurado, Kyle, Sydney K. Ludvigson and Serena Ng. 2015. Measuring Uncertainty. American Economic Review 105(3), 1177-1216.

[34] Justiniano, Alejandro, Primiceri, Giorgio E., Tambalotti, Andrea, 2010. Investment shocks and business cycles. Journal of Monetary Economics 57 (2), 132–145.

[35] Justiniano, Alejandro, Primiceri, Giorgio E., Tambalotti, Andrea, 2011. Investment Shocks and the Relative Price of Investment. Review of Economic Dynamics 14 (1), 101–121.

[36] Kiyotaki, Nobuhiro, and John Moore, 1997, Credit cycles, Journal of Political Economy 105, 211-248.

[37] Kraft, Holger, Eduardo S. Schwartz and Farina Weiss. 2013. Growth Options and Firm Valuation. NBER Working Paper No. 18836.

[38] Kydland, Finn E.; Prescott, Edward C. 1982. Time to Build and Aggregate Fluctuations. Econometrica 50(6), 1345-70.

[39] Laeven, Luc and Fabian Valencia. 2013. Systemic Banking Crises Database. IMF Economic Review 61, 225–270.

[40] Lanteri, Andrea. 2016. The Market for Used Capital: Endogenous Irreversibility and Reallocation over the Business Cycle. Mimeo: Duke University.

[41] Lee, Yoonsoo and Toshihiko Mukoyama. 2012. Entry, Exit, and Plant-level Dynamics over the Business Cycle. Mimeo: University of Virginia.

[42] Ma, Xiaohan and Roberto Samaniego. 2016. Uncertain Technology. Mimeo: George Washington University.

[43] Mulligan, Casey B. and Xavier Sala-i-Martin. 1997. A labor income-based measure of the value of human capital: An application to the states of the United States. Japan and the World Economy 9(2), 159-191.

[44] Nunn, Nathan, 2007, Relationship-specificity, incomplete contracts, and the pattern of trade, Quarterly Journal of Economics, 569-600.

[45] Oi, Walter Y. 1961. The Desirability of Price Instability under Perfect Competition. Econometrica 29(1), 58–64.

[46] Rajan, Raghuram G. and Luigi Zingales, 1998, Financial dependence and growth, American Economic Review 88, 559-586.

[47] Samaniego, Roberto M. 2008. Entry, Exit and Business Cycles in a General Equilibrium Model. Review of Economic Dynamics 11(3), 529-541.

[48] Samaniego, Roberto M. 2010. Entry, Exit and Investment-Specific Technical Change. American Economic Review 100(1), March 2010, 164-192.

[49] Samaniego, Roberto M. and Juliana Y Sun. 2015. Technology and Contractions: Evidence from Manufacturing. European Economic Review 79, 172-195.

[50] Samaniego, Roberto M. and Juliana Y Sun. 2016. Productivity growth and structural transformation. Review of Economic Dynamics 21, 266-285.

[51] Stokey, Nancy L. 2016. Wait-and-See: Investment Options under Policy Uncertainty. Review of Economic Dynamics 21, 246-65.

[52] Veracierto, Marcelo L. 2002. Plant-Level Irreversible Investment and Equilibrium Business Cycles. American Economic Review 92(1), 181-197.

[53] Wooldridge, Jeffrey M. 2002. *Econometric analysis of cross section and panel data.* MIT Press, Cambridge, MA.

A Econometric procedure

We estimate a case of the following model

$$Y_{ict} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + X_{ict}\beta + \varepsilon_{ict} \tag{3}$$

where i is industry, c is a country, t is a year. The coefficients $\delta_{i,c}$, $\delta_{i,t}$ and $\delta_{c,t}$ are regression coefficients on indicator variables for (i,c), (i,t) and (c,t) pairs respectively. We have that $c \in \{1, C\}$, $t \in \{1, T\}$ and $i \in \{1, N\}$. Also, the panel is unbalanced, so the number of observations is not $C \times T \times N$. C is the total number of countries, T year and N the total number of industries. X_{ict} is a vector of independent variables $[X_{ict1}\ X_{ict2}...]'$.

In order to estimate (3), we transform it so as to eliminate $\delta_{i,c}$, $\delta_{i,t}$ and $\delta_{c,t}$. First , we define the mean of Y_{ict} and X_{ict} by i, c, t. We use the "dot" notation for means for brevity.

For example, $\overline{Y}_{ic.}$ is the mean of Y_{ict} averaging over different values of t. $\overline{Y}_{i.t}$ is the mean of Y_{ict} by c. $\overline{Y}_{...}$ is the mean by i, c and t. Thus,

$$\overline{Y}_{ic.} = \frac{1}{T_{ic}} \sum_{t=1}^{T_{ic}} Y_{ict}$$

$$\overline{Y}_{i.t} = \frac{1}{C_{it}} \sum_{c=1}^{C_{it}} Y_{ict}$$

$$\overline{Y}_{.ct} = \frac{1}{N_{ct}} \sum_{i=1}^{N_{ct}} Y_{ict}$$

$$\overline{Y}_{i..} = \frac{1}{C_{it}} \frac{1}{T_{ic}} \sum_{c=1}^{C_{it}} \sum_{t=1}^{T_{ic}} Y_{ict}$$

$$\overline{Y}_{..t} = \frac{1}{N_{ct}} \frac{1}{C_{it}} \sum_{i=1}^{N_{ct}} \sum_{c=1}^{C_{it}} Y_{ict}$$

$$\overline{Y}_{.c.} = \frac{1}{T_{ic}} \frac{1}{N_{ct}} \sum_{t=1}^{T_{ic}} \sum_{i=1}^{N_{ct}} Y_{ict}$$

$$\overline{Y}_{...} = \frac{1}{T_{ic}} \frac{1}{N_{ct}} \frac{1}{C_{it}} \sum_{c=1}^{C_{it}} \sum_{t=1}^{T_{ic}} \sum_{i=1}^{N_{ct}} Y_{ict}$$

Similarly ,

$$\overline{X}_{ic.} = \frac{1}{T_{ic}}\sum_{t=1}^{T_{ic}} X_{ict}$$

$$\overline{X}_{i.t} = \frac{1}{C_{it}}\sum_{c=1}^{C_{it}} X_{ict}$$

$$\overline{X}_{.ct} = \frac{1}{N_{ct}}\sum_{i=1}^{N_{ct}} X_{ict}$$

$$\overline{X}_{i..} = \frac{1}{C_{it}}\frac{1}{T_{ic}}\sum_{c=1}^{C_{it}}\sum_{t=1}^{T_{ic}} X_{ict}$$

$$\overline{X}_{..t} = \frac{1}{N_{ct}}\frac{1}{C_{it}}\sum_{i=1}^{N_{ct}}\sum_{c=1}^{C_{it}} X_{ict}$$

$$\overline{X}_{.c.} = \frac{1}{T_{ic}}\frac{1}{N_{ct}}\sum_{t=1}^{T_{ic}}\sum_{i=1}^{N_{ct}} X_{ict}$$

$$\overline{X}_{...} = \frac{1}{T_{ic}}\frac{1}{N_{ct}}\frac{1}{C_{it}}\sum_{c=1}^{C_{it}}\sum_{t=1}^{T_{ic}}\sum_{i=1}^{N_{ct}} X_{ict}$$

Similar notation applies to $\delta_{i,c}$, $\delta_{i,t}$ and $\delta_{c,t}$.

First, we subtract the average over t, so that (3) becomes (notice the terms δ_{ic} are gone):

$$Y_{ict} - \overline{Y}_{ic.} = \left(X_{ict} - \overline{X}_{ic.}\right)' \beta + \left(\delta_{it} - \overline{\delta}_{i.}\right) + \left(\delta_{ct} - \overline{\delta}_{c.}\right) + \left(\varepsilon_{ict} - \overline{\varepsilon}_{ic.}\right) \tag{4}$$

Then de-mean (4) over c, yielding

$$\overline{Y}_{i.t} - \overline{Y}_{i..} = \left(\overline{X}_{i.t} - \overline{X}_{i..}\right)' \beta + \left(\delta_{it} - \overline{\delta}_{i.}\right) + \left(\overline{\delta}_{.t} - \overline{\delta}_{..}\right) + \left(\overline{\varepsilon}_{i.t} - \overline{\varepsilon}_{i..}\right) \tag{5}$$

Then subtract (5) from (4) (notice δ_{it} is gone) :

$$Y_{ict} - \overline{Y}_{ic.} - \overline{Y}_{i.t} + \overline{Y}_{i..} = \left(X_{ict} - \overline{X}_{ic.} - \overline{X}_{i.t} + \overline{X}_{i..}\right)' \beta + \left(\delta_{ct} - \overline{\delta}_{c.} - \overline{\delta}_{.t} + \overline{\delta}_{..}\right) + \left(\varepsilon_{ict} - \overline{\varepsilon}_{ic.} - \overline{\varepsilon}_{i.t} + \overline{\varepsilon}_{i..}\right) \tag{6}$$

Now we de-mean (6) over i :

$$\overline{Y}_{.ct} - \overline{Y}_{.c.} - \overline{Y}_{..t} + \overline{Y}_{...} = \left(\overline{X}_{.ct} - \overline{X}_{.c.} - \overline{X}_{..t} + \overline{X}_{...}\right)' \beta + \left(\delta_{ct} - \overline{\delta}_{c.} - \overline{\delta}_{.t} + \overline{\delta}_{..}\right) + \left(\varepsilon_{.ct} - \overline{\varepsilon}_{.c.} - \overline{\varepsilon}_{..t} + \overline{\varepsilon}_{...}\right) \tag{7}$$

Then subtract (7) from (6)(notice δ_{ct} is gone):

$$
\begin{aligned}
& Y_{ict} - \overline{Y}_{ic.} - \overline{Y}_{i.t} + \overline{Y}_{i..} - \overline{Y}_{.ct} + \overline{Y}_{.c.} + \overline{Y}_{..t} - \overline{Y}_{...} \\
& = \left(X_{ict} - \overline{X}_{ic.} - \overline{X}_{i.t} + \overline{X}_{i..} - \overline{X}_{.ct} + \overline{X}_{.c.} + \overline{X}_{..t} - \overline{X}_{...}\right)' \theta \\
& + \left(\varepsilon_{ict} - \overline{\varepsilon}_{ic.} - \overline{\varepsilon}_{i.t} + \overline{\varepsilon}_{i..} - \varepsilon_{.ct} + \overline{\varepsilon}_{.c.} + \overline{\varepsilon}_{..t} - \overline{\varepsilon}_{...}\right)
\end{aligned} \tag{8}
$$

Thus, we can rewrite (8) *in the following form, and estimate the following equation:*

$$
\begin{aligned}
\widetilde{Y}_{ict} &= \widetilde{X'}_{ict} \beta + \widetilde{\varepsilon}_{ict} \\
\text{where } \widetilde{Y}_{ict} &= Y_{ict} - \overline{Y}_{ic.} - \overline{Y}_{i.t} + \overline{Y}_{i..} - \overline{Y}_{.ct} + \overline{Y}_{.c.} + \overline{Y}_{..t} - \overline{Y}_{...} \\
\widetilde{X}_{ict} &= X_{ict} - \overline{X}_{ic.} - \overline{X}_{i.t} + \overline{X}_{i..} - \overline{X}_{.ct} + \overline{X}_{.c.} + \overline{X}_{..t} - \overline{X}_{...} \\
\widetilde{\varepsilon}_{ict} &= \varepsilon_{ict} - \overline{\varepsilon}_{ic.} - \overline{\varepsilon}_{i.t} + \overline{\varepsilon}_{i..} - \varepsilon_{.ct} + \overline{\varepsilon}_{.c.} + \overline{\varepsilon}_{..t} - \overline{\varepsilon}_{...}
\end{aligned} \tag{9}
$$

We can estimate β using:

$$
\widehat{\beta} = \left(\widetilde{X'}_{ict} \widetilde{X}_{ict}\right)^{-1} \widetilde{X}_{ict} \widetilde{Y}_{ict}
$$

and the standard errors using:

$$
\begin{aligned}
& \left(\#^{-1} \widetilde{X'}_{ict} \widetilde{X}_{ict}\right)^{-1} \frac{1}{\sqrt{\#}} \widetilde{X'}_{ict} \widetilde{\varepsilon}_{ict} \\
& = \left(\#^{-1} \widetilde{X'}_{ict} \widetilde{X}_{ict}\right)^{-1} \frac{1}{\sqrt{\#}} \sum_{c=1}^{C_{it}} \sum_{t=1}^{T_{ic}} \sum_{i=1}^{N_{ct}} \widetilde{X}_{ict} \widetilde{\varepsilon}_{ict}
\end{aligned}
$$

where # is the total number of observations.

In our paper, we estimate the transformed form (9) instead of (3) in the two-stage least square regressions. In the first stage ,X_{ict} is a vector of $[IV_{c,t} \times X_i \ Controls_{i,c,t}]'$. $IV_{c,t}$ include natural disaster shocks, political shocks, revolution shocks and terrorist shocks. Y_{ict} is the uncertainty measure that we instrumented for.

Then in the second stage, we use the estimated $\widetilde{Y}_{ict}$ from (9) and control variables as a new $\widehat{X}_{ict}$ vector of $\left[\widetilde{Y}_{ict} \ Controls_{i,c,t}\right]'$ and Y_{ict} is the industry growth variable. That is, we estimate the following:

$$
Y_{ict} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \widehat{X}_{ict} \beta + \varepsilon_{ict}
$$

using the demean method again. So that, we can rewrite the estimation equation as

$$
\begin{aligned}
\widetilde{\widetilde{Y}}_{ict} &= \widetilde{\widetilde{X'}}_{ict}\beta + \widetilde{\varepsilon}_{ict} \qquad (10)\\
\text{where } \widetilde{\widetilde{Y}}_{ict} &= Y_{ict} - \overline{Y}_{ic.} - \overline{Y}_{i.t} + \overline{Y}_{i..} - \overline{Y}_{.ct} + \overline{Y}_{.c.} + \overline{Y}_{..t} - \overline{Y}_{...}\\
\widetilde{\widetilde{X}}_{ict} &= \widehat{X}_{ict} - \overline{\widehat{X}}_{ic.} - \overline{\widehat{X}}_{i.t} + \overline{\widehat{X}}_{i..} - \overline{\widehat{X}}_{.ct} + \overline{\widehat{X}}_{.c.} + \overline{\widehat{X}}_{..t} - \overline{\widehat{X}}_{...}\\
\widetilde{\varepsilon}_{ict} &= \varepsilon_{ict} - \overline{\varepsilon}_{ic.} - \overline{\varepsilon}_{i.t} + \overline{\varepsilon}_{i..} - \varepsilon_{.ct} + \overline{\varepsilon}_{.c.} + \overline{\varepsilon}_{..t} - \overline{\varepsilon}_{...}
\end{aligned}
$$

We can thus estimate β using:

$$
\widehat{\beta} = \left(\widetilde{\widetilde{X'}}_{ict}\widetilde{\widetilde{X}}\right)^{-1}\widetilde{\widetilde{X}}_{ict}\widetilde{\widetilde{Y}}_{ict}
$$

In general since we do not know the distribution of ε_{ict} we do not know the distribution of $\widetilde{\varepsilon}_{ict}$ either. We test various distributions for $\widetilde{\varepsilon}_{ict}$, including bootstrap, clustering and allowing for serially correlated errors. We find that our results are robust to various distributions of $\widetilde{\varepsilon}_{ict}$. In the paper, we report results using bootstrapped errors.