

# Do Business Cycles Affect Patenting? Evidence from European Patent Office Filings

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## Abstract

This paper studies the sensitivity of patent filings to the business cycle using patent filings at the European Patent Office (EPO). Using a dynamic model of patenting and the Hodrick-Prescott (HP) filter method to separate the cyclical component of real Gross Domestic Product (GDP) from its trend component, we find that patent filings are strongly pro-cyclical. This supports the view that short term resource constraints affect patenting decisions, even if there are longer term factors that determine innovation. The study also has significance for forecasting patenting behavior, which is important for policy decision-making, institutional operations, and strategic business planning. Forecasts that rely only on trends prove to be less accurate amidst economic booms and recessionary shocks, such as the recent global financial crisis.

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# 1 Introduction

Two key issues motivate this paper: do business cycles affect patenting behavior and if so, is patenting pro-cyclical or counter-cyclical? Earlier, Griliches (1990) had observed the effects of oil shocks during the 1970s on patent applications. Likewise, the Great Recession of 2008 and 2009 has spurred interest in the impact of cyclical shocks on patenting.<sup>1</sup> The relationship matters to institutional organizations that operate the global patenting system, such as national and regional patent offices, and to industries that provide complementary services to the patenting community; for example, legal, translation, and consulting services. Cyclical shocks affect the ability of these organizations to forecast accurately for purposes of planning and budgeting. Such shocks can therefore affect the supply of services and resources for patent procurement. Cyclical shocks can also affect the demand side by influencing the investment and marketing decisions of firms and other potential patentees. The resulting imbalances in supply and demand could thus have repercussions for the nature and direction of innovation and commercialization.<sup>2</sup>

Much of the existing literature studying the determinants of patents and patenting propensity has not taken into account the role of cyclical shocks.<sup>3</sup> Patents and innovation are often studied under the branch of economic growth theory, as drivers of long run productivity and technological change, where the emphasis is more on structural determinants and trend factors than on cyclical influences. Furthermore, innovation is viewed by many as being driven by longer term considerations, given that the duration of innovation projects is often longer than that of market cycles (see Heger, 2004). On the other hand, short run resource constraints may be binding for some innovators as patenting is costly, and the costs of procurement are often incurred upfront before a patented invention is exploited commercially.

The literature on the relationship between innovation and business cycles is very limited, as will be surveyed in the next section. Few academic studies exist, focusing mostly on the input side of innovation namely, research and development (R&D) expenditures. Research on

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<sup>1</sup>See, for example, Bertenrath et al. (2011), Guellec and Wunsch-Vincent (2009), European Commission (2011), OECD (2009), and WIPO (2010).

<sup>2</sup>See, for example, Meade and Islam (2006).

<sup>3</sup>See Danguy et al. (2014), de Rassenfosse and van Pottelsberghe de la Potterie (2007), de Rassenfosse and van Pottelsberghe de la Potterie (2012), Hall (2005), Hu and Jefferson (2009), Kortum and Lerner (1998), Liu et al. (2014), Park (1999), Sanyal and Jaffe (2005), Scherer (1983), and Thumm (2001).

the effects of business cycles on patenting is rarer. Furthermore, previous work has not formally derived and used a measure of business cycles, and instead has employed proxy variables, such as credit constraints or sales declines (although business cycles also include sales booms), or has compared conditions before and/or after an event, such as the Great Recession of 2008–2009. In this paper, we derive business shocks using standard filtering methods, and allow them to vary by country. A key novelty of our paper is that we apply our business cycle model to forecasting patent filings. This would especially be useful to the *supply side* we mentioned earlier. Failure to anticipate fluctuations leads these institutions and service providers to allocate resources poorly. Improved forecasting can lead to more accurate budgeting and greater cost effectiveness in services, and these increased efficiencies should potentially raise social welfare.

Using data on patent filings at the European Patent Office (EPO), this study provides evidence on the impacts of shocks to gross domestic product (GDP) on the patent filing behavior of 28 countries (including a rest-of-the-world group) over a span of more than three decades. The EPO is a regional patent institution representing a large market area. It provides a single patent granting procedure for its Member Contracting States. A patent granted through the EPO represents a bundle of national patents.

This paper is organized as follows. The next section 2 briefly reviews the existing literature on business cycles and innovation. Section 3 presents the patenting model and discusses the methodology. Section 4 describes the data, and section 5 presents the main results and robustness checks. Section 6 provides an application to forecasting EPO patent filings, and section 7 concludes. Overall, EPO filings are found to be sensitive to business cycles, but the effects of cyclical shocks on filings eventually dissipate. Even so, the cyclical disturbances pose significant challenges for predicting patenting behavior.

## 2 Previous Literature

The existing literature has identified two opposing effects of business cycles on innovation activity: the *resource effect* and the *opportunity cost effect*. The resource effect is that, in a booming

economy, firms have more resources, or access to resources, for innovation. Firms typically rely mostly on internal resources, such as cash flow or retained earnings, to fund research projects, and secondarily on external sources, such as venture capital financing or subsidies and grants from the public sector. Both internal and external resources are more easily available when the economy is in an expansionary phase than in a contractionary one. Under the resource effect, innovation is pro-cyclical; that is, it increases when the economy is growing and decreases when it is declining. The opportunity cost effect states that innovation will increase when the economy is in a downturn. The reasons are two-fold. First, the cost of conducting research is lower during a recession. Research input costs, such as the price of materials and labor, will be lower. Second, the opportunity cost of conducting research is lower during a recession. Allocating resources to innovation will require diverting resources and effort away from production and marketing activities, but when the economy is in a downturn, the loss in sales is not too high. In contrast, when the economy is booming, firms face a higher opportunity cost of diverting time and resources away from production in order to engage in innovation. Under the opportunity cost effect, therefore, innovation is counter-cyclical falls when the economy is growing and rises when the economy is contracting.

Few studies have tested the effects of business cycles on innovation. As a typology, they consist of both microeconomic studies using firm or industry level data and macroeconomic studies using country level data. Studies vary as to whether the dependent variable is R&D or patenting. Most of these focus on R&D as the measure of innovation. Rafferty and Funk (2008), for example, use firm level data for U.S. manufacturing industries from 1973–1990 and find that the opportunity cost effect is weak so that, overall, R&D is pro-cyclical. Their dependent variable is the growth rate of R&D, which they regress on measures of business cycles, such as sales rising (or falling), and cash flow rising (or falling). A limitation of these measures is that part of the movement in sales and cash flow can be due to shifts in the long term trend as well as to short term cycles. Another issue is whether it is appropriate to measure business cycle shocks using firm level variables, rather than say macroeconomic or industrial level variables. Fluctuations in firm sales, for example, need not be the outcome of business cycle shocks.

Lopez-Garcia et al. (2012), in contrast, find support for the opportunity cost effect. Using

a large sample of Spanish firms from 1991–2009, the authors find R&D to be counter-cyclical, provided that credit constraints are absent. They argue that firms utilize economic downturns to invest in productivity-enhancing activities, such as R&D and on-the-job training. Their regression equation relates changes in R&D to changes in GDP, changes in cash flow, and other variables. Again, mere changes in GDP and cash flow are not good measures of the business cycle, as they consist of changes in both the trend and cyclical components of income.

A study that does focus on patenting and business cycles is Martinsson and Lf (2009). They study a sample of Swedish firms in the manufacturing industry from 1997–2005 in order to examine how a firm's patenting is affected by its cash flow. Fluctuations in cash flow are their proxy for business cycles (the limitation of which was discussed above). The authors find that cash flow shocks affect patenting only during economic downturns, but not during expansions. Hence, they find partial support for the resource effect, suggesting that patenting is pro-cyclical only when there is a recession. Giedeman et al. (2006) also study the effects of business cycles on patenting but for U.S. firms. They find that patenting by small firms in the semiconductor industry is pro-cyclical, while that in the automobile industry is countercyclical. The former industry tends to manufacture high-tech goods of relatively low durability whereas the latter industry produces durable consumer goods. In earlier work, Geroski and Walters (1995) examined counts of major U.K. innovations (namely, those that were commercial successes), as well as the patent filings of U.K. firms in the U.S., and found innovation activity to be pro-cyclical.

There are also a few macroeconomic studies on the effects of business cycles on innovation (see European Commission, 2011; Guellec and Wunsch-Vincent, 2009; OECD 2009; and World Intellectual Property Organization, 2010). Their analyses are based on what happened to innovation during the Great Recession. In a study on the impacts of public R&D and tax incentives on private research, Guellec and van Pottelsberghe de la Potterie (2003) use GDP growth as a control for business cycles. In this paper, we derive a more explicit measure of cyclical shocks and test their effects on innovation across a longer time horizon and across regions. Spatial differences in shocks can be used to determine whether variations in innovation are attributable to business cycles or to some other related global phenomena. To date, the literature has found little evidence for the opportunity cost hypothesis. Our multi-country panel

data analysis further supports the view that patenting is pro-cyclical.

### 3 Empirical Model and Methodology

Since patents are sought for new technological innovations, we expect patenting to relate to innovation activities. Innovation in turn is a function of the investments in R&D and the size of the market. Let  $f(R, Y)$  be a function describing innovation output, where  $R$  denotes expenditures on business R&D and  $Y$  is gross domestic product, as a measure of the aggregate market. The basic model of patenting is then given by

$$P^* = f(R, Y)e^{\nu} \quad (1)$$

where  $P^*$  denotes the long run equilibrium or steady-state level of patenting. The exponential function  $e^{\nu}$  is a stochastic term representing the random component of patenting.

Equation (1) is a steady-state model. As argued in de Rassenfosse and van Pottelsberghe de la Potterie (2012), patenting does not immediately adjust to its steady state level. Innovation projects may be spread out over time and innovation may be cumulative and sequential. Patent filers may also gain experience with the filing of patent applications related to their innovations. To allow for a dynamic process in patenting, it is assumed that the *distance* of patenting from its steady-state level is closed partially in each period; that is, the current level of patenting is between the previous periods level and the long run, steady-state level. For example,

$$\frac{P}{\ell(P)} = \left( \frac{P^*}{\ell(P)} \right)^{\psi} \quad 0 < \psi < 1 \quad (2)$$

where  $\ell(P)$  is lagged patenting and  $\psi$  a parameter measuring the speed of adjustment. In steady state,  $P = \ell(P) = P^*$ .

We assume that the innovation function can be parameterized as  $f(R, Y) = \phi R^{\beta} Y^{\gamma}$ ,<sup>4</sup> and that lagged patents are a weighted aggregate of past patents:  $\ell(P) = \prod_{j=1}^k P_{-j}^{\eta_j}$ , subject to

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<sup>4</sup>We adopt a Cobb-Douglas specification so that we can derive a log-linear relationship between  $P$  and  $R$  that is common in the literature see Griliches (1990).

$\sum_{j=1}^k \eta_j = 1$ , and where  $k = 2$  is chosen (based on pre-testing of the significance of lags). Substituting these into (1) and then into (2) yields a patenting equation in levels:

$$\ln P = \alpha_0 + \alpha_1 \ln P_{-1} + \alpha_2 \ln P_{-2} + \alpha_3 \ln R + \alpha_4 \ln Y + \epsilon \quad (3)$$

where  $\epsilon$  is the error term and the  $\alpha$  coefficients are functions of previously defined parameters.<sup>5</sup>

We next introduce business cycles. In equation (3),  $Y$  represents GDP, which can be decomposed as follows:  $Y = Y^T + Y^C$ , where  $Y^T$  denotes the trend level of output and  $Y^C$  the cyclical component. The trend component is positive, but the cyclical component can be positive or negative. The natural log of  $Y$  then is  $\ln Y = \ln(Y^T + Y^C) = \ln(Y^T(1 + \frac{Y^C}{Y^T})) = \ln Y^T + \ln(1 + \frac{Y^C}{Y^T})$ . The business cycle variable can be defined as:

$$u = \frac{Y^C}{Y^T}$$

which is the ratio of cyclical GDP to trend GDP. Consequently,  $\ln Y = \ln Y^T + \ln(1 + u)$ . But  $\ln(1 + u) \approx u$  for values of  $u$  in the neighborhood of zero (which applies to the data here); therefore, the natural log of GDP can be decomposed as  $\ln Y = \ln Y^T + u$ . Substituting this into (3) gives us the business-cycle augmented patenting model:

$$\ln P = \alpha_0 + \alpha_1 \ln P_{-1} + \alpha_2 \ln P_{-2} + \alpha_3 \ln R + \alpha_4 \ln Y^T + \alpha_5 u + \epsilon \quad (4)$$

We derive  $u$  by using the Hodrick and Prescott (1997) filtering method (henceforth HP method). Appendix A provides a brief background on the HP method. The essence of the method is to derive a weighted moving average of GDP that is symmetric and centered as the measure of trend GDP, and the deviations of actual GDP from trend as the cyclical component. Since we use annual data, we follow Ravn and Uhlig (2002) and choose  $\lambda = 6.25$ , where  $\lambda$  is a parameter which governs how much weight is given to trend shifts versus cycles, based on their relative variances in the data.<sup>6</sup>

<sup>5</sup>For instance,  $\alpha_0 = \psi \ln \phi$ ,  $\alpha_1 = \eta_1(1 - \psi)$ ,  $\alpha_2 = \eta_2(1 - \psi)$ ,  $\alpha_3 = \psi\beta$ ,  $\alpha_4 = \psi\gamma$ , and  $\epsilon = \psi\nu$ . Note also that in equation (3), R&D is contemporaneous to patenting. Alternatively, R&D could be lagged a few periods to allow for R&D to affect patentable innovations with a lag (as done in Hingley and Park, 2015).

<sup>6</sup>For example, if  $\lambda = 0$ , all movements in output are assumed to be movements in the trend. If  $\lambda \rightarrow \infty$ , all movements in output are due to deviations from trend. Thus, an intermediate value of  $\lambda$  allows for output

Next, we re-write the model in *intensive units* by dividing all the variables by the number of workers,  $L$ , before taking logarithms. This helps us deal with scale effects whereby economies with larger human resources tend to have greater patentable inventions. In addition, we control for country effects, year dummies, and country-specific time trends. The country effects control for country heterogeneity in EPO filings, the year dummies help control for unobserved common factors that shift over time, and the country-specific time trends help pick up secular drifts that vary by source country. We therefore have the following

$$\ln\left(\frac{P}{L}\right)_{it} = \alpha_i + \alpha_t + \tau_{it} + \alpha_1 \ln\left(\frac{P}{L}\right)_{it-1} + \alpha_2 \ln\left(\frac{P}{L}\right)_{it-2} + \alpha_3 \ln\left(\frac{R}{L}\right)_{it} + \alpha_4 \ln\left(\frac{Y^T}{L}\right)_{it} + \alpha_5 u + \epsilon_{it} \quad (5)$$

where the country effects are given by the vector  $\alpha_i$ , the year effects by  $\alpha_t$ , and the country-specific linear time trends by  $\tau_{it}$ . Note that  $u$  is not affected by the size of the labor force since  $u$  is a ratio of cyclical GDP to trend GDP.<sup>7</sup>

Furthermore, we first-difference the model. This helps mitigate problems with non-stationarity in the patenting series, which has been documented elsewhere (see Hall, 2005). It also allows us to control for more unobserved heterogeneity.

$$\Delta \ln\left(\frac{P}{L}\right)_{it} = \delta_i + \alpha_t + \alpha_1 \Delta \ln\left(\frac{P}{L}\right)_{it-1} + \alpha_2 \Delta \ln\left(\frac{P}{L}\right)_{it-2} + \alpha_3 \Delta \ln\left(\frac{R}{L}\right)_{it} + \alpha_4 \Delta \ln\left(\frac{Y^T}{L}\right)_{it} + \alpha_5 \Delta u + \varepsilon_{it} \quad (6)$$

where  $\varepsilon_{it} = \epsilon_{it} - \epsilon_{it-1}$ ,  $\Delta \ln\left(\frac{P}{L}\right)_{it} = \ln\left(\frac{P}{L}\right)_{it} - \ln\left(\frac{P}{L}\right)_{it-1}$ , and so forth. Note that country effects,  $\delta_i$ , are still present in the differenced model as a result of first-differencing the country-specific time trends,  $\tau_{it}$ , in equation (5).

The dynamic panel data model, given by equation (6), is our basic estimation model, which we estimate by the system-Generalized Method of Moments (GMM), as fixed effects estimates would be biased and inconsistent in the presence of a lagged dependent variable.<sup>8</sup>

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changes to be a mixture of business cycles and changes in trend output. The larger the value of  $\lambda$ , the smoother is the path of trend output.

<sup>7</sup>For example,  $\ln \frac{Y}{L} = \ln\left(\frac{Y^T}{L} + \frac{Y^C}{L}\right) = \ln\left(\frac{Y^T}{L}\left(1 + \frac{Y^C}{Y^T}\right)\right) = \ln \frac{Y^T}{L} + \ln(1 + u) \approx \ln \frac{Y^T}{L} + u$ .

<sup>8</sup>See Arellano and Bond (1991) and Blundell and Bond (1998) for details. We have also estimated the level version – equation (5) – via GMM and have estimated equation (6), without the country fixed effects, via OLS, and found the qualitative results to be similar. These results are available upon request.



The consistency of GMM estimation depends on the instruments being valid (i.e. no correlation between the error term and the instruments) and on the absence of second order serial correlation in the first differences of the residuals; both assumptions are tested using the Sargan-Hansen (SH) and Arellano-Bond (AB) tests respectively.

It is important to note that our patenting model (6) does not exhaustively consider all the important determinants of patenting. For example, patenting costs or fees could also influence the patenting decision (see Park, 1999; de Rassenfosse and van Pottelsberghe de la Potterie, 2007; and de Rassenfosse and van Pottelsberghe de la Potterie, 2012). Appropriability, patent quality, and strategic factors, such as the extent of patent thickets, could also play a role (see Danguy et al., 2014). Our choice of independent variables was based on a few practical considerations related to implementing the model for forecasting purposes. Certain factors, like EPO fees, do not change frequently and are rather difficult to anticipate.

## 4 Data Description

This study employs *annual data* on patent filings at the European Patent Office (EPO), excluding divisional filings (since they exhibit volatility due to rule changes at various time points).<sup>9</sup> While it would also be desirable to analyze business cycles at shorter frequencies, say monthly or quarterly periods, particularly since recessions are identified when GDP declines in two consecutive quarters (or six months), we concentrate on annual data for pragmatic purposes since it is standard forecasting practice at the EPO to work with annual filings. A further reason is that the duration of business cycles often exceeds a year (see Burns and Mitchell, 1946 and Baxter and King, 1999).

We focus on total filings at the EPO. These are the sum of direct filings at the EPO and filings that come to the EPO via the international phase of the Patent Cooperation Treaty

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<sup>9</sup>Note that the use of EPO data may obscure any substitution effects, whereby applicants file in other EPC offices (e.g. France or Germany) in response to shocks. However, filings at major national offices in Europe as well as at other offices such as the Japanese Patent Office (JPO), Korean Intellectual Property Office (KIPO), and United States Patent and Trademark Office (USPTO) have also tended to follow the decline observed in the EPO during the Great Recession. See, for example, the statistical tables associated with the IP5 Statistics report: <http://www.fiveipoffices.org/statistics/statisticsreports/2013edition.html>.

(PCT) system.<sup>10</sup> Each of these components is the sum of first and subsequent filings (i.e., patents that were first filed at some other patent office).<sup>11</sup> Our EPO filings data are not a comprehensive measure of a country's priority filings worldwide,<sup>12</sup> but neither are they limited to priority filings in national patent offices. Many but not all EPO filings start out as priority applications in national patent systems, but first filings are also made at the EPO. It is possible that first filings (wherever they are made) may be less dependent on business cycles because they measure the output of earlier research rather than indications of willingness to exploit commercially. But subsequent filings do show more intent of commercial application and these make up most of the EPO filings.<sup>13</sup>

The sample consists of a panel dataset of 28 applicant countries, including a rest-of-the-world (ROW) group: Australia, Austria, Belgium, Brazil, Canada, China (including Hong Kong), Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, Taiwan, United Kingdom, United States, and ROW. The 27 main countries in the sample (excluding ROW) account for the bulk of global R&D and patenting in the EPO. Our sample period is 1978–2013. The patent data come primarily from the EPO and the World Intellectual Property Organization (WIPO), the R&D data from the OECD, and the rest from the International Monetary Fund (IMF) and the World Bank. Table 1 provides a summary of the data sources.

Table 2 presents some sample correlations among the key variables. The table shows positive correlations among business cycles, trend GDP, R&D, and EPO filings, but a low correlation exists between movements in cycles and movements in trend GDP, which we take as a good sign that our decomposition method isolated an independent source of variation in output.

As a precursor to our regression analyses, Figures 1 and 2 show the path of business cycles and EPO filings, respectively, for the five major patenting source countries of the EPO. While

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<sup>10</sup>The PCT international phase filings are as reported by WIPO. Another possibility, not further pursued here, is to use regional phase PCT filings. See Hingley and Park (2015) for more details.

<sup>11</sup>Later we check to see whether first filings are affected differently by cyclical shocks than subsequent filings.

<sup>12</sup>See, for example, de Rassenfosse et al., 2013, which constructs a patent indicator based on all priority patent applications by inventor country, wherever they are filed first.

<sup>13</sup>The differential effects of business cycles on first and subsequent filings are shown in Section 5.

these figures do not control for other influences, they provide a visual look at the significant drop in EPO filings around the time of the 2008–2009 global financial crisis, and a drop in filings for Japan and the U.S. during the recessionary period of 2003. These figures are therefore suggestive of some potential relationship between cyclical shocks and patenting.

## 5 Empirical Results

Our main results on business cycles and EPO filings are in Table 3. Table 4 provides some robustness checks by examining alternative ways to measure business cycles and Table 5 examines filings broken by first filings and subsequent filings. After these regression analyses, we apply the model in section 6 to conduct some pseudo out-of-sample forecasting experiments in order to gauge the consequences of ignoring business cycles when predicting patent filings.

Column 1 of Table 3 shows a statistically significant association between cyclical movements in GDP and changes in EPO filings per worker, with an elasticity of about 1.15. This result indicates that business fluctuations have a pro-cyclical effect on patent filings, controlling for other factors. Changes in trend GDP per worker are also a significant factor, as are changes in R&D per worker. The lagged dependent variables have coefficients that are negative and less than one in absolute value. This is consistent with the lagged dependent variables having a positive coefficient that is between zero and one if the model were in log-levels, which in turn indicates some persistence in filings that dampens over time.

Column 2 of Table 3 controls for membership in the EPO. Since we are studying patent filings at the EPO and since most of the countries in the sample are EPO members, it would be useful to know if they exhibit different variations in filing intensities. In other work, de Rassenfosse and van Pottelsberghe de la Potterie (2007) finds that among European Patent Convention (EPC) member states, the duration of membership positively affects the transfer of domestic priority filings to the EPO, which captures the effects of familiarity with the European patent system. However, in our case, EPO members do not have significantly different growth paths in EPO filings than non-members.

In column 3, we check whether the results thus far are driven primarily by the 2008–2009 global financial crisis. EPO filings fell significantly during this period, as shown in Figure 2. We do this by interacting the business cycle variable with a dummy variable which equals one for the years 2008 and 2009 (and zero otherwise). We find that the coefficient estimate on the change in  $u$  (or  $\Delta \frac{Cycles}{Trend}$ ) remains significantly positive. The interaction between the financial crisis dummy and changes in the business cycle indicator, however, is insignificant. In other words, the response of EPO filings growth to business cycle shocks was not proved to be any different than in other cyclical episodes. The drop in EPO filings was large because of the severity of the recession during 2008–9, while there did not seem to have been any behavioral difference in innovation and patenting.

Column 4 repeats the analysis in Column 1 by estimating the model over a shorter period (1978–2005), without year effects. The motivation is that we will later use this model to conduct out-of-sample forecasting tests for 2006–2013, and this would be a good moment to show what the forecasting model looks like. The estimates of the model are fairly ‘stable’ between Columns 1 and 4. The year dummies are excluded here because they are specific to the in-sample period and are not applicable outside it.

Table 4 turns to an important issue: to what extent are our findings due to the measure of business cycles? An alternative to the HP-filter method is the Baxter and King (2009) approach.<sup>14</sup> We can also proxy economic fluctuations by shifts in the unemployment rate. We drew shocks to the unemployment rate (for each country) by regressing the rate on a time trend and using the fitted residuals as our measure of these shocks. These two alternative measures of business cycles largely confirm our finding that EPO filings per worker are significantly procyclical (see columns 1 and 2). For example, the Baxter-King filter method also shows that business cycle movements have a highly procyclical effect on changes in EPO filings. Thus, the results we have obtained so far seem not to be sensitive to the filtering method. Another confirmation that business cycles matter is that the coefficient estimate of the unemployment variable is significantly negative, meaning that when unemployment rates are higher, as during a recession, patenting intensity grows more slowly, holding other factors constant.

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<sup>14</sup>Appendix A provides more details on the Baxter-King approach.

Thus far we have only decomposed GDP into its trend and cycle. It is also possible to filter out the cyclical and trend components of R&D. This is shown in column 3 of Table 4. We find that changes in EPO filings per worker respond insignificantly to movements in cyclical R&D. In column 4 of Table 4, we include both the changes in cyclical R&D and the changes in cyclical GDP. The explanatory power of movements in cyclical GDP remains strong. Thus it appears that the effects of business cycles on EPO filings operate through the overall market (i.e., GDP) rather than through the R&D sector.

Table 5 shows the last regression analysis that involves assessing whether business cycles affect first (priority) filings differently from subsequent filings. Our EPO filings up to now have combined these two filings for each calendar year. Approximately 15% of the EPO filings during the sample period were first filings. However, the share of first filings in the EPO has increased from about 9% in 1978 to 17% by 2011. As we discussed earlier, subsequent filings may reflect a greater willingness of firms or inventors to exploit their innovations commercially, and therefore may be especially impacted by market fluctuations. Table 4 reveals that cyclical shocks predominantly affect subsequent filings activities (compare columns 1 and 2).<sup>15</sup> We obtain the same findings if we use the Baxter-King filtering method for deriving cyclical shocks (see columns 3 and 4).

## 6 Experiment

Policy authorities and users of patented technology often need to consider the future outlook for innovation when making critical policy or private decisions. It is especially in this sphere of forecasting where the decomposition of GDP into its trend and cycle is crucial. Most professional forecasters tend to forecast trend GDP only often giving a straight line projection. While there is a burgeoning literature on predicting cycles or recessions, these models largely focus on turning points that is, use probit models to predict when a recession (or boom) will occur, but not how deeply.<sup>16</sup> Of course, predicting cycles is typically much harder than predicting longer

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<sup>15</sup>This was a robustness check and is not a conclusive result for Europe since first filings can also be made at national patent offices that are distinct from the EPO.

<sup>16</sup>See, for example, the International Monetary Fund (IMF) *World Economic Outlook Database* (<https://www.imf.org/external/pubs/ft/weo/2014/02/weodata/index.aspx>) and the Conference Board *Global*

term trends. Nonetheless, a forecast of trend GDP alone could be very limiting for purposes of making predictions about future patenting, particularly in situations where business and policy decisions are contingent on the realization of economic shocks.

In this section, we evaluate the consequences of omitting business cycles when making forward-looking projections about patenting. The basic method is to estimate the model up to 2005, and then use the estimated model to conduct pseudo out-of-sample forecasts of EPO filings for the period 2006 - 2013. We *pretend* that we are in 2005 and try to simulate the conditions under which policymakers and businesses would anticipate future patenting. Such forecasters would predict the trend in GDP and anticipate business cycles under conditions of imperfect information and uncertainty. To evaluate the success of such forecasting, we compare the forecasts not only to the actual filings that emanated but also to predictions of the model under other scenarios, including where forecasters have exact information about the future path of GDP and cyclical shocks. The reason is that there is model uncertainty as well as uncertainty about the path of future output.<sup>17</sup>

In order to focus sharply on the role of forecasting future output on the accuracy of predicting EPO filings, we assume complete knowledge of the other variables that we control for, such as R&D and labor. However, we do perform *dynamic* forecasting, where instead of using the actual values of EPO filings as inputs for the lagged dependent variables in the patenting model, we input the fitted (predicted) values of the filings, except in the case of forecasting patenting in 2006 and 2007, where we would know (if we were situated in 2005) the actual values of EPO filings in 2004 and 2005.

Our forecasting model is the fitted equation of (6) without the time dummies (since we are forecasting out-of-sample). We then feed this estimated model with projections of trend GDP

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*Economic Outlook* (<https://www.conference-board.org/data/globaloutlook>).

<sup>17</sup>For work on model uncertainty, see Lahiri, Peng, and Sheng (2013).

and  $u$  (where  $u = \frac{Cycles}{Trend}$ ), both of which are estimated using a simple AR2 model:<sup>18</sup>

$$\hat{Y}_{it}^T = \hat{\beta}_0 + \hat{\beta}_1 \hat{Y}_{it-1}^T + \hat{\beta}_2 \hat{Y}_{it-2}^T \quad (7)$$

$$\hat{u}_{it} = \hat{\rho}_0 + \hat{\rho}_1 \hat{u}_{it-1} + \hat{\rho}_2 \hat{u}_{it-2} \quad (8)$$

We obtained fitted equations (7) and (8) separately for each country using the sample data up to 2005. We then used equations (7) and (8) to generate a set of predicted series  $\{\hat{Y}_{it}^T\}$  and  $\{\hat{u}_{it}\}$  for 2006 - 2013.<sup>19</sup> The predicted series were then inputted into equation (6) to generate forecasts of the changes in the natural log of patents per worker. We then converted the fitted changes into log-levels. The predicted log-levels of filings per worker are assumed to be lognormally distributed. These then have to be transformed accordingly into natural units and multiplied by the number of workers to obtain the *predicted levels* of EPO filings. Appendix B provides details on the transformation process of deriving the mean and standard errors of the predictions.

To demonstrate the value of incorporating forecasts of business cycles when performing out-of-sample forecasts of patenting, we examine the following four cases: 1) actual values of trend GDP and  $u$ , the business cycle indicator, are assumed for the out-of-sample period (2006 - 2013); 2) forecasted values of trend GDP, generated by equation (7), and no cycles are assumed; 3) forecasted values of trend GDP, generated by equation (7), and forecasted cycles, generated by equation (8), are assumed; 4) conditions similar to case 3 are assumed, except that we introduce a large adverse shock to the business cycle indicator,  $u$ , equal to three times the worst recessionary period that occurred in a country during the sample period (up to 2005).

Specifically, in the adverse shock scenario, a discrete jump in  $u$  occurs in 2009. The value of  $u$  in 2009 is equal to thrice the minimum of  $\{u_{1978}, \dots, u_{2005}\}$  and is country-specific. Thereafter, the values of the  $u$  vector are generated by the same fitted equation  $\hat{u} = \hat{\rho}_0 + \hat{\rho}_1 \hat{u}_1 + \hat{\rho}_2 \hat{u}_2$ ,

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<sup>18</sup>Our AR2 model of cyclical shocks is a simple approach, used for its tractability. For ongoing research on forecasting business cycles, see the special issue on the topic (Ferrara and van Dijk, 2014). Recent research focuses on methods for predicting turning points, selecting business cycle indicators, deriving short-medium term forecasts, and measuring predictive uncertainty. A well-known result from the research appears to be that it is not easy to improve upon the linear AR model (Ferrara and van Dijk, 2014, p. 519).

<sup>19</sup>Note that equation (8) presumes no further shocks or disturbances to  $u$  during the out-of-sample period. Any disturbances prior to 2006 are allowed to run their course through the out-of-sample period.

generating a new path of  $u$ :  $\{\hat{u}'_{2010}, \dots, \hat{u}'_{2013}\}$ .

The *Root Mean Square Percentage Error (RMSPE)* criterion will be used as the metric for assessing forecast accuracy:

$$RMSPE_t = \sqrt{\frac{1}{T} \sum_{t=1}^T \left( \frac{\hat{P}_t - P_t}{P_t} \right)^2}$$

where  $\hat{P}_t = \sum_{i=1}^N \hat{P}_{it}$  is the total predicted filings across countries and  $P_t = \sum_{i=1}^N P_{it}$  the total actual filings across those countries.

Table 6 provides a summary of the forecast accuracy by year under each case. Table 7 summarizes the forecasted values of EPO filings, along with their standard errors. The best performance is associated with Case 1 where the forecaster has complete knowledge of the future values of trend GDP and business cycles  $u$ . Across all years, the root mean squared percentage error (RMPSE) is 0.112. Even with knowledge of the actual values of trend GDP and  $u$ , the model makes a huge forecast error in 2009. As Table 7 indicates, the model still over-predicts actual filings by well more than 10,000. This shows that the patenting model we use is, of course, imperfect and not able to capture all of the variations in EPO filings.

Case 2 shows the worst performance in terms of forecast accuracy during the years 2008 - 2010. This is an example where professional forecasters only provide forecasts of trend GDP, while ignoring business cycles. Case 3 shows an improvement over Case 2 (in the sense of generating greater forecast accuracy). This is an example where the professional forecaster also makes forecasts of the business cycle indicator, albeit imperfectly using an AR2 model of  $u$ . Still, in case 3, the forecast performance is not as good as in case 1 where knowledge of the actual cycle exists.

Finally, let us build on Case 3, where in 2005, we make projections of trend GDP and the business cycle over the period 2006 - 2013. We know from Table 7 that even in this case, the forecaster makes a huge error in predicting EPO filings for 2009. The actual filings were about 204,000, but the model predicts nearly 234,000, about 30,000 more than actually occurred. But suppose the forecaster had some inkling that 2008 - 2009 would experience some severe



global financial shock and that the AR2 model of  $u$  would not pick that up. What size of a shock to  $\{u_{it}\}$  could the forecaster anticipate? In theory, the forecaster should form rational expectations of  $\{u_{it}\}$ , incorporating all available information. In practice, the forecaster may look to recent history and choose shocks that are consistent with past experience. We follow the latter approach. Instead of selecting a shock to  $\{u_{it}\}$  that replicates the drop in EPO filings in 2009 – the size of which would not be known to the forecaster in 2005 – we impose a shock value and then trace its effects. Specifically, in our case, we make the value of  $u_{it}$  in 2009 equal to three times the minimum value of  $u_{it}$  that occurred in a country during 1978 - 2005. This past minimum value, again, varies by country. For perspective, the minimum value of  $u_{it}$  is, for the average country, about twice the standard deviation of  $u_{it}$  during the 1978 - 2005 period.

As Table 7 shows (Case 4), the shock causes the predicted value of EPO filings indeed to fall towards the actual filings for 2009. But as Table 6 shows, the RMSPE overall is only marginally better than that of Case 3 and not as good as Case 1. In other words, the ad-hoc approach to assigning a large anticipated adverse shock in 2009 does not improve forecast accuracy all that much over the whole out-of-sample period. Indeed, the forecast design under Case 4 yields a path similar to that under Case 3 after 2010. Thus, making ad-hoc short-run shock adjustments to the forcing variables (Case 4) is not appreciably better than simply forecasting trend GDP and forecasting the path of the business cycle indicator,  $u$  (Case 3). In other words, tweaking the forecasted path of  $u$  does not necessarily improve overall forecast accuracy. The intuition is that business cycle shocks, in our illustration, are ultimately temporary. For the entire eight years of the out-of-sample period, the total filings under Cases 3 and 4 are similar (about 1,930,000 filings) and lower than the case where cyclical fluctuations are ignored (Case 2).

The key lessons here are: i) business cycles should be forecasted, not just trend GDP, for purposes of projecting patenting behavior (compare Case 2 and Case 3); ii) ad-hoc shock adjustments would not improve overall predictability if ultimately cyclical shocks are transitory (compare Case 3 and Case 4); and iii) predictions of patent filings will be inaccurate even if we had actual knowledge of trend GDP and business cycles (message of Case 1), as there still is model uncertainty. In that sense, the better benchmark for comparing the scenarios in Cases 2 - 4 is not the actual filings, but the filings in Case 1. Overall, our experiments recommend

forecasters to utilize forecasts of both cycles and trend GDP (as in Case 3).

## 7 Conclusion

This paper has provided a dynamic panel data analysis of patent filings and business cycles. Thus far, limited empirical studies have been conducted on the relationship between patenting and business fluctuations. Moreover, prior work has not applied methods for distinguishing between market trends and cycles, such as filtering methods that extract cyclical shocks from movements in a time-series, but has relied instead on ad-hoc, informal measures of shocks. By applying more rigorous methods to a broad panel dataset of source countries of the EPO, this paper finds that the response of patent filings to GDP shocks is quite elastic and pro-cyclical, lending support to the *resource effect* of business cycles on innovation. The findings are also robust to alternative measures of business cycles, and thus do not depend on the HP-filtering method we adopted. The sensitivity of patent filings to business cycles is also no different during the global financial crisis of 2008 - 2009 than during the rest of the sample period. Lastly, some out-of-sample forecasting experiments show that incorporating business cycles can help improve the accuracy of predicting patenting behavior. They show, however, that while GDP shocks can result in significant perturbations in patenting, the effects of cyclical shocks on patenting are short-lived.

This paper has practical significance for forecasting future patenting. Many institutions, such as national and regional patent offices, rely on patent forecasts for budgetary and resource allocation purposes. Businesses that provide supporting services, such as patent representatives, and multinational firms that make important strategic and competitive decisions, also depend upon accurately forecasting innovative activities. But few, if any, patent forecasting models to date have incorporated business cycles. A related study, Hingley and Park (2015), further explores true out-of-sample forecasting of EPO filings for 2014 - 2019.<sup>20</sup>

This paper can be extended in a number of directions. Firstly, it has implications for further

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<sup>20</sup>This study finds that booms and recessions change filings by about  $\pm 2.2\%$ . In the present paper, we find that the cyclical shock in 2009 is associated with a 3.1% drop in filings (compare Cases 3 and 4 for 2009), but the recession during 2009 was of a more severe nature than considered in Hingley and Park (2015).

helping with the practical problem of forecasting future patent filings for budgetary planning purposes at patent offices.<sup>21</sup> Secondly, in light of the findings in this paper, it would be useful to conduct more studies on how firms innovate amid cyclical fluctuations, especially since the costs of innovation and patenting are generally front-loaded while the returns to innovation backloaded. Thirdly, the effects of business cycles on patenting could be analyzed using higher frequency data, such as monthly or quarterly. Fourthly, the effects of business cycles could be studied using more disaggregated data, such as at the inventor or firm level.

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<sup>21</sup>Kim and Lee (2015) compare the databases of different patent offices. Our methods could be adapted to forecasting filings at other offices.

## 8 Appendix

### A. Notes on Filtering

Under the Hodrick and Prescott (1997) filtering method, the natural log of the trend component of output (or GDP) is chosen to minimize the following objective function:

$$\min_{\{Y_t^T\}} \sum_{t=1}^{\tau} (Y_t - Y_t^T)^2 + \lambda (\Delta^2 Y_t^T)^2$$

subject to  $Y_t = Y_t^T + Y_t^C$  for all  $t = 1 \dots \tau$ . Here,  $\Delta^2$  is the second-difference operator, so that:

$$(\Delta^2 Y_t^T) = \Delta(\Delta Y_t^T) = \Delta Y_t^T - \Delta Y_{t-1}^T = (Y_t^T - Y_{t-1}^T) - (Y_{t-1}^T - Y_{t-2}^T)$$

Substituting this into the above loss function provides a useful way to interpret the objective function:

$$\min_{\{Y_t^T\}} \sum_{t=1}^{\tau} (Y_t - Y_t^T)^2 + \lambda ((Y_t^T - Y_{t-1}^T) - (Y_{t-1}^T - Y_{t-2}^T))^2$$

The first term,  $(Y_t - Y_t^T)^2$ , is the squared deviations of  $Y$  from trend, and the second term,  $(Y_t^T - Y_{t-1}^T) - (Y_{t-1}^T - Y_{t-2}^T)$ , is the *change* in the growth rate of trend and captures the smoothness of the trend. To see this, note that  $Y$ s are in natural logs, so that  $g_t^T = Y_t^T - Y_{t-1}^T$ , is the growth rate of  $Y^T$  between time  $t$  and  $t-1$ , and  $g_{t-1}^T = Y_{t-1}^T - Y_{t-2}^T$ , the growth rate of  $Y^T$  between time  $t-1$  and  $t-2$ . The second term is thus essentially  $\Delta g_t^T$ , the shifts in the trend growth rate. The parameter  $\lambda$  determines how much weight is given to trends relative to cycles. If both of these terms are identically and independently distributed with mean zero and variance  $\sigma_1$ ,  $\sigma_2$  respectively, then  $\lambda = \frac{\sigma_1}{\sigma_2}$  where  $\sigma_1 = \text{var}(Y_t - Y_t^T)$  and  $\sigma_2 = \text{var}(\Delta^2 Y_t^T)$ .

The HP method is a class of high-pass filters in that it removes the trend (low frequency cycles) and retains the high frequency ones. The Baxter and King (1999) (henceforth BK) approach is a band-pass filter. It removes frequencies that are both too low and too high to be classified as a business cycle, under their definition, and retains those in-between. Their adopted definition of a business cycle is one where the cyclical components are no less than 18 months in duration and no more than 8 years in duration. Their filtering method preserves the timing of turning points; that is, avoids inducing phase shifts. The BK approach drops observations at the beginning and end of the sample period equal to the symmetric lead and lag length ( $K$ ) of the filter.

BKs filter is  $Y_t = \sum_{j=-K}^K a_j (L^j Y_t)$ , where  $Y$  denotes GDP and  $L$  the backshift operator. The cyclical component is the two-sided moving average  $Y_t^C = \sum_{j=-K}^K a_j (L^j (Y_{t+j}) - \mu)$ , where  $\mu$  denotes the mean. The question is how to select the weights  $a_j$ . First, the BK approach imposes a constraint that the sum of the moving average coefficients be zero; i.e.,  $\sum_{j=-K}^K a_j = 0$ . Then, subject to this constraint, the  $a_j$ 's are chosen to minimize the following objective function, expressed in the frequency domain:

$$\int_{-\pi}^{\pi} |\Psi(\omega) - Y(\omega)|^2$$

where  $\omega$  represents frequency and  $(-\pi, \pi)$  the range of frequencies.  $Y(\omega)$  is the Fourier transform

mation of the BK filter in the frequency domain and  $\Psi(\omega)$  the *ideal* filter. Essentially,  $Y(\omega)$  is an approximation of  $\Psi(\omega)$ . Both  $Y(\omega)$  and  $\Psi(\omega)$  are functions of  $a_j$ .

## B. Notes on Experiment

The model used to predict EPO filings out-of-sample is equation (6), but the fitted variables are in changes in the natural logarithms of patents per worker. Hence, we transform the fitted variables in order to back out the levels of the predicted filings in natural units. The dependent variable is  $pl = \ln \frac{P}{L}$ , where  $P$  denotes patent filings and  $L$  labor.  $pl$  is assumed to be normally distributed with mean  $\mu$  and variance  $\sigma^2$ :  $pl \sim N(\mu, \sigma^2)$

As shown in Johnson and Kotz (1972), the mean of  $\frac{P}{L}$  is  $E(\frac{P}{L}) = e^{\mu+0.5\sigma^2}$  and the variance of  $\frac{P}{L}$  is  $\gamma^2(e^{\sigma^2} - 1)$ , where  $\gamma = e^{\mu+0.5\sigma^2}$ . We therefore obtain the predicted levels of filings to be:

$$\hat{P} = L e^{\hat{pl}+0.5\hat{s}^2}$$

with an estimated variance of

$$var(\hat{P}) = L^2 e^{2(\hat{pl}+0.5\hat{s}^2)} (e^{\hat{s}^2} - 1)$$

where  $\hat{s}^2$  is the sample variance of  $pl$ . Therefore, the total predicted patent filings across all  $N$  countries each year,  $t$ , is:  $\sum_{i=1}^N \hat{P}_{it}$ .

For the variance (or standard error) of predicted filings across all countries, we take into account the covariances in the log of filings between pairs of countries  $i$  and  $j$ :

$$cov(pl_i, pl_j) = e^{(\mu_i+\mu_j+0.5(\sigma_{ii}+\sigma_{ij}))} (e^{\sigma_{ij}} - 1)$$

Let  $\Sigma$  be the  $N \times N$  matrix of the covariances of all pairs of countries. The variance of total predicted patent filings is then:<sup>22</sup>

$$var\left(\sum_{i=1}^N \hat{P}_{it}\right) = \sum_{i=1}^N L_{it} \sum_{j=1}^N L_{jt} (\hat{\gamma}_{it} \hat{\gamma}_{jt}) (e^{\Sigma_{ij}} - 1)$$

The standard error, or the square root of the above estimated variance, is shown in Table 7.

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<sup>22</sup>See Hingley and Park (2015) for further details.

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Table 1: **Variables and Data Sources**

Variable Name	Source
Patent Filings (P)	European Patent Office (EPO), EPASYS; World Intellectual Property Office (WIPO), www.wipo.int/ipstats/en/statistics/pct/
Gross Domestic Product (Y)	World Bank, <i>World Development Indicators</i>
Business Enterprise R&D Funding (R)	Organization for Economic Cooperation and Development (OECD); United Nations Educational, Scientific, and Cultural Organization, www.uis.unesco.org
Labor (L)	World Bank, <i>World Development Indicators</i>
Unemployment Rates	World Bank, <i>World Development Indicators</i> ; International Monetary Fund, <i>International Financial Statistics</i>
Exchange Rates, PPP Conversion	Penn World Tables, pwt.sas.upenn.edu; International Monetary Fund, <i>International Financial Statistics</i>

Table 2: **Cross-correlations**

Variables	$\Delta \ln \frac{EPO \text{ Filings}}{Worker}$	$\Delta \ln \frac{Trend \text{ GDP}}{Worker}$	$\Delta \frac{Cycles}{Trend}$	$\Delta \ln \frac{R\&D}{Worker}$
$\Delta \ln \frac{EPO \text{ Filings}}{Worker}$	1.000			
$\Delta \ln \frac{Trend \text{ GDP}}{Worker}$	0.163	1.000		
$\Delta \frac{Cycles}{Trend}$	0.128	0.037	1.000	
$\Delta \ln \frac{R\&D}{Worker}$	0.112	0.339	0.252	1.000

Table 3: Main Results

Dependent Var	(1) $\Delta \ln \left( \frac{EPO \ Filings}{Worker} \right)$	(2) $\Delta \ln \left( \frac{EPO \ Filings}{Worker} \right)$	(3) $\Delta \ln \left( \frac{EPO \ Filings}{Worker} \right)$	(4) $\Delta \ln \left( \frac{EPO \ Filings}{Worker} \right)$
$\Delta \ln \left( \frac{EPO \ Filings}{Worker} \right)_{-1}$	-0.375*** (0.029)	-0.375*** (0.029)	-0.376*** (0.029)	-0.259*** (0.029)
$\Delta \ln \left( \frac{EPO \ Filings}{Worker} \right)_{-2}$	-0.084*** (0.026)	-0.083*** (0.026)	-0.084*** (0.026)	0.064*** (0.022)
$\Delta \ln \left( \frac{Trend \ GDP}{Worker} \right)$	1.085** (0.493)	1.000** (0.496)	1.102** (0.493)	1.043* (0.568)
$\Delta \left( \frac{Cycles}{Trend} \right)$	1.147** (0.496)	1.127** (0.496)	1.280** (0.517)	1.039** (0.484)
$\Delta \ln \left( \frac{R\&D}{Worker} \right)$	0.340*** (0.125)	0.342*** (0.125)	0.337*** (0.125)	0.420*** (0.154)
EPO Member Dummy		-0.057 (0.048)		
Finan. Crisis Dummy x $\Delta \left( \frac{Cycles}{Trend} \right)$			-1.671 (1.854)	
Constant	-14.156*** (4.323)	-13.723*** (4.323)	-13.967*** (4.326)	0.217 (0.277)
Year Effects	Included	Included	Included	Excluded
AB Test (p-value)	0.16	0.14	0.15	0.17
SH Test (p-value)	0.18	0.18	0.17	0.13
Observations	922	922	922	698

Notes: Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. The sample period is 1978-2013, except in column (4) where it is 1978-2005. The estimation method is System Generalized Method of Moments. The AB Test is the Arellano-Bond test of no 2nd-order autocorrelation in the first differences of the residuals and the SH Test is the Sargan-Hansen Overidentification Test of no correlation between the instruments and the error term. The Financial Crisis Dummy equals one during the years 2008 - 2009, zero otherwise.

Table 4: **Alternative Shocks**

Dependent Var	(1) $\Delta \ln \left( \frac{EPO \text{ Filings}}{Worker} \right)$	(2) $\Delta \ln \left( \frac{EPO \text{ Filings}}{Worker} \right)$	(3) $\Delta \ln \left( \frac{EPO \text{ Filings}}{Worker} \right)$	(4) $\Delta \ln \left( \frac{EPO \text{ Filings}}{Worker} \right)$
$\Delta \ln \left( \frac{EPO \text{ Filings}}{Worker} \right)_{-1}$	-0.369*** (0.034)	-0.389*** (0.031)	-0.373*** (0.029)	-0.381*** (0.029)
$\Delta \ln \left( \frac{EPO \text{ Filings}}{Worker} \right)_{-2}$	-0.126*** (0.032)	-0.135*** (0.028)	-0.090*** (0.027)	-0.092*** (0.026)
$\Delta \ln \left( \frac{Trend \text{ GDP}}{Worker} \right)$	0.765 (0.566)	1.060* (0.595)	0.951* (0.524)	0.867* (0.520)
$\Delta \ln \left( \frac{R\&D}{Worker} \right)$	0.347** (0.135)	0.365*** (0.130)		
$\Delta \left( \frac{Cycles}{Trend} \right)_{Baxter-King}$	1.528*** (0.551)			
<i>Unemploy. Rate Shocks</i>		-0.009* (0.005)		
$\Delta \left( \frac{R\&D \text{ Cycles}}{R\&D \text{ Trend}} \right)$			0.172 (0.153)	0.066 (0.157)
$\Delta \ln \left( \frac{R\&D \text{ Trend}}{Worker} \right)$			0.575** (0.257)	0.649** (0.256)
$\Delta \left( \frac{Cycles}{Trend} \right)$				1.412*** (0.501)
Constant	5.118 (9.931)	-1.735 (1.946)	-13.476*** (4.343)	-13.950*** (4.305)
Year Effects	Included	Included	Included	Included
Observations	781	792	922	922
AB Test (p-value)	0.50	0.15	0.19	0.13
SH Test (p-value)	0.06	0.07	0.22	0.11

*Notes:* Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. The sample period is 1978-2013. The estimation method is System Generalized Method of Moments. The AB Test is the Arellano-Bond test of no 2nd-order autocorrelation in the first differences of the residuals and the SH Test is the Sargan-Hansen Overidentification Test of no correlation between the instruments and the error term. The Baxter-King filtering method is discussed in the text. Unemployment rate shocks are deviations of the rate from trend. R&D cycles were obtained by applying the HP filter to real R&D expenditures.

Table 5: EPO Filings Breakdown

Dependent Var	(1) $\Delta \ln \left( \frac{\text{First Filings}}{\text{Worker}} \right)$	(2) $\Delta \ln \left( \frac{\text{Subsequent Filings}}{\text{Worker}} \right)$	(3) $\Delta \ln \left( \frac{\text{First Filings}}{\text{Worker}} \right)$	(4) $\Delta \ln \left( \frac{\text{Subsequent Filings}}{\text{Worker}} \right)$
$\Delta \ln \left( \frac{\text{First Filings}}{\text{Worker}} \right)_{-1}$	-0.375*** (0.032)		-0.399*** (0.035)	
$\Delta \ln \left( \frac{\text{First Filings}}{\text{Worker}} \right)_{-2}$	-0.032 (0.030)		-0.073** (0.032)	
$\Delta \ln \left( \frac{\text{Subsequent Filings}}{\text{Worker}} \right)_{-1}$		-0.305*** (0.030)		-0.330*** (0.034)
$\Delta \ln \left( \frac{\text{Subsequent Filings}}{\text{Worker}} \right)_{-2}$		-0.037 (0.028)		-0.088*** (0.031)
$\Delta \ln \left( \frac{\text{Trend GDP}}{\text{Worker}} \right)$	0.812 (0.969)	1.094** (0.545)	1.102 (1.059)	0.714 (0.589)
$\Delta \left( \frac{\text{Cycles}}{\text{Trend}} \right)$	1.137 (0.936)	1.454*** (0.525)		
$\Delta \left( \frac{\text{Cycles}}{\text{Trend}} \right)_{\text{Baxter-King}}$			0.779 (1.011)	1.790*** (0.564)
$\Delta \ln \left( \frac{\text{R\&D}}{\text{Worker}} \right)$	0.286 (0.234)	0.430*** (0.133)	0.304 (0.244)	0.469*** (0.138)
Constant	-1.420 (1.682)	-2.404 (8.783)	5.685 (5.235)	-13.296 (18.381)
Year Effects	Included	Included	Included	Included
Observations	896	896	782	782
AB Test (p-value)	0.13	0.13	0.38	0.38
SH Test (p-value)	0.03	0.22	0.90	0.12

Notes: Standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. The sample period is 1978-2013. The estimation method is System Generalized Method of Moments. The AB Test is the Arellano-Bond test of no 2nd-order autocorrelation in the first differences of the residuals and the SH Test is the Sargan-Hansen Overidentification Test of no correlation between the instruments and the error term.

Table 6: **Out of Sample Filing Forecasts: Forecast Accuracy**

Root Mean Squared Percentage Error (RMSPE)				
<b>year</b>	<b>Case 1</b>	<b>Case 2</b>	<b>Case 3</b>	<b>Case 4</b>
2006	0.089	0.078	0.089	0.089
2007	0.112	0.092	0.106	0.106
2008	0.094	0.098	0.093	0.093
2009	0.123	0.166	0.151	0.128
2010	0.127	0.147	0.131	0.122
2011	0.116	0.103	0.121	0.120
2012	0.120	0.121	0.129	0.133
2013	0.113	0.135	0.127	0.128
<b>Total</b>	<b>0.112</b>	<b>0.118</b>	<b>0.118</b>	<b>0.115</b>

<sup>a</sup> Model estimated up to 2005 is used to forecast filings for 2006-2013. During the out-of-sample period, actual values of R&D per worker are used. In addition:

<sup>b</sup> Case 1 assumes actual values of trend and cyclical GDP during the out-of-sample period.

<sup>c</sup> Case 2 uses forecasted trend GDP and assumes no GDP cycles during the out-of-sample period.

<sup>d</sup> Case 3 uses forecasted trend GDP and forecasted GDP cycles during the out-of-sample period.

<sup>e</sup> Case 4 is similar to Case 3, except an additional shock is introduced in 2009, equal to three times a country's largest adverse business cycle value ( $u$ ) during 1978 - 2005.

Table 7: Out of Sample Filings Forecasts: Predicted Means and Standard Errors

Year	Actual	Case 1	Case 2	Case 3	Case 4
	Filings				
2006	203940	214914 (7260)	216464 (7609)	211244 (7123)	211244 (7123)
2007	215493	226717 (8583)	231133 (8296)	225411 (7799)	225411 (7799)
2008	218756	233153 (8871)	242834 (8964)	237748 (8450)	237748 (8450)
2009	204609	219859 (8861)	238831 (8852)	233831 (8294)	226398 (9397)
2010	214482	229808 (7742)	233734 (8554)	229266 (8006)	232346 (8425)
2011	234324	237034 (8490)	240433 (9250)	242502 (8760)	248157 (8877)
2012	248165	258482 (9556)	265040 (10421)	265306 (9988)	267838 (10372)
2013	257456	268445 (9999)	284567 (11507)	287044 (11014)	286048 (11378)
Total	1797225	1888412 (24636)	1953036 (26176)	1932352 (24773)	1935191 (25653)

Standard errors are in parentheses. See also notes to Table 6.

Figure 1. Business Cycle Index (Cycles/Trend): Selected Countries

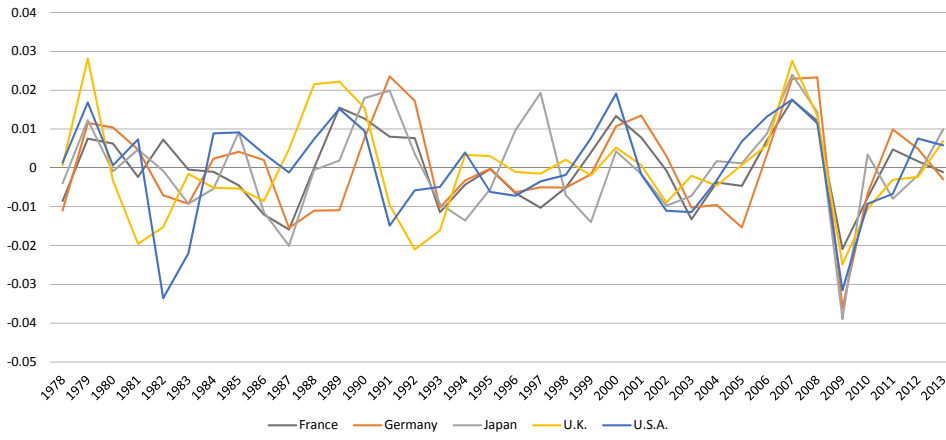


Figure 2. European Patent Office (EPO) Patent Filings: Direct plus Euro via PCT International Phase Filings

