General Purpose Technologies, International Technology Diffusion, and the Cross Section of Stock Returns

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JEL Classification: G12, O33, G15

Keywords: *cross section of stock returns; general purpose technologies; innovation; international asset pricing*

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1. Introduction

General purpose technologies (GPTs) refer to a class of inventions that are widely used in many productive activities and generate pervasive impacts on the aggregate economy (Bresnahan and Trajtenberg 1995).[1] Major GPTs since the industrial revolution include the steam engine, electricity, computers, and internet, among others (Lipsey, Carlaw, and Clifford 2005). As a prominent example, information technologies, encompassing electronics, computers, communications, and the internet, have revolutionized production processes and reshaped the global economy since the 1960s and are regarded as the major GPT in recent decades (Greenwood and Jovanovic 1999; Brynjolfsson and Hitt 2000; Hobijn and Jovanovic 2001; Jovanovic and Rousseau 2005).

Through international technology diffusion (Grossman and Helpman 1991; Howitt 2000; Keller 2004), GPTs developed in one country can also impact the aggregate productivity and consumption of other countries. Developed economies such as G-7 have been the major driving force for technology changes due to their higher R&D investments and more supportive institutional environments; for the rest of the world, foreign sources of technologies contribute to 90 percent or more of domestic productivity growth (Keller 2004). Through cross-border spillovers, GPTs play an important role in the dynamics of cross-country productivity, economic, and income growth (Aghion and Howitt 1998; Keller 2002; Jones 2005).

In this paper, we propose and empirically test the hypothesis that GPTs are a source of non-diversifiable risk to U.S. and global investors. Given the wide uses of GPTs in productive activities and their pervasive impacts on the aggregate economy, existing asset pricing theory provides economic intuition for the pricing of GPT risk in stock returns. The investment-based

[1] See Helpman (1998), Jovanovic and Rousseau (2005), Lipsey, Carlaw, and Clifford (2005), and Bresnahan (2010) for surveys of the literature on GPTs.

asset pricing model of Cochrane (1996) shows that the stochastic discount factor is a function of aggregate investment return. The pervasive effects of GPTs suggest that their shocks drive aggregate productivity and aggregate investment return to vary over time. In consumption-based asset pricing models (e.g., Breeden 1979, Hansen and Singleton 1982, and Breeden, Gibbons, and Litzenberger 1989), the pricing kernel is a function of consumption growth. A positive relation between GPTs and aggregate consumption arises because GPTs generate persistent effects on aggregate productivity, and persistent technology growth leads to higher consumption (Campbell 1994). Furthermore, through technology spillovers, GPTs developed in one economy may increase the aggregate productivity and consumption in another economy. Taken together, both investment- and consumption-based asset pricing models suggest that GPT risk should be priced, i.e., exposure to GPT risk should be compensated, in both U.S. and international stock markets.

We construct empirical GPT risk factors using U.S. patent data, and use standard two-stage cross-sectional regressions to estimate the risk premiums for GPT risk in stock portfolios.[2] The estimated risk premiums range from about 15% per year in U.S. stock returns for the period of 1963-2006 to about 4% to 8% per year in international stock returns for the period of 1991-2006 (the shorter international sample is a result of data availability). We also evaluate the contribution of GPT risk in explaining the cross section of stock returns. Exposure to GPT risk accounts for a substantial fraction of the cross-sectional variation in stock returns — more than 75% for U.S. stock returns, and between 50% and 80% for international stock returns.

Our empirical GPT risk factors are based on the number of patents granted by the U.S. Patent and Trademark Office (USPTO) each year for the period 1963-2006. Our approach

[2] Our test assets are Fama-French portfolios formed on size and the book-to-market ratio, which are readily available for both the U.S. (Fama and French 1993) and the international stock markets (Fama and French 2012). These portfolios exhibit substantial dispersion in average returns and have been extensively used in asset pricing tests.

follows the view in the literature that U.S. patent data reflect the accumulation of important technologies in both the U.S. and the rest of the world (e.g., Griffith, Harrison, and Van Reenen 2006; Acharya and Subramanian 2009; Hsu, Tian, and Xu 2014). This view seems reasonable because the U.S. has been the largest market for high-tech products over the past half century, and, due to the territoriality principle in patent laws, foreign inventors who want to protect their inventions in the U.S. must file for U.S. patents.

All the patents are classified by Hall, Jaffe and Trajtenberg (2001) into six technology categories: (1) chemical, (2) computer and communications, (3) drugs and medical, (4) electrical and electronic, (5) mechanical, and (6) others. Following the consensus in the literature, we define categories 2 and 4 as GPT patents, and categories 1, 3, 5, and 6 as specific purpose technology (SPT) patents. The growth rates of GPT and SPT patents are positively correlated. This is consistent with innovation complementarity, another defining feature of GPTs emphasized in the literature, which suggests that GPTs enable innovations in application technologies and vice versa (Bresnahan and Trajtenberg 1995). In contrast to GPTs, SPTs influence a narrower range of sectors and their shocks are likely diversifiable. Thus, the positive correlations between GPT and SPT growth rates suggest that part of the variations in GPT patent growth rates are driven by SPT shocks and are diversifiable.

Based on these observations, we construct an empirical proxy for non-diversifiable GPT risk as the difference between the average of the two GPT patent growth rates and the average of the four SPT patent growth rates. We find that this empirical GPT factor is highly and significantly positively correlated with the GPT patent growth rates, but almost uncorrelated with the SPT patent growth rates. In addition, this GPT factor is pro-cyclical: it is positively correlated with U.S. consumption, GDP, and industrial production growth. Further, it forecasts the cumulative growth rates of U.S. consumption, GDP, and industrial production over horizons of the following three years. These findings are consistent with the intuition of the investment- and consumption-based asset pricing models, and provide support to the proposed GPT factor as reflecting non-diversifiable GPT risk.[3] The empirical GPT factor is also positively correlated with all Fama-French (1993) three factors of U.S. stock returns, suggesting the possibility that the Fama-French factors may capture non-diversifiable technology risk.

We then conduct asset pricing tests to examine whether the GPT factor is priced in the cross section of U.S. stock returns over the sample period of 1963-2006. For the Fama-French 25 portfolios formed on size and the book-to-market ratio, the single GPT factor model is able to explain the cross section of average excess returns with an R^2 of 75.8%. The estimated factor risk premium is 14.8% per year and is strongly significant. The null hypothesis that all pricing errors are jointly zero is not rejected. The GPT betas of the Fama-French 25 portfolios match the well-known size and value premiums: small firms have higher GPT betas than large firms, and value (high book-to-market ratio) firms have higher GPT betas than growth (low book-to-market ratio) firms. The performance of the single GPT factor is almost comparable to the R^2 of 82.7% generated by the Fama-French three-factor model. Furthermore, when we estimate a model that includes both the GPT factor and the Fama-French three factors, the GPT factor remains significantly priced. Hence, the GPT factor captures information and contributes explanatory power above and beyond conventional return-based factors.

Overall, our results point to the economic significance of the GPT factor, which is significantly priced in and accounts for a substantial fraction of the cross-sectional variation of U.S. stock returns. The asset pricing performance of the GPT factor is noteworthy given that it is

[3] The differencing approach also mitigates the effects of potential regulation and institutional changes that affect the growth rates of patents in all technology categories.

not a return-based factor, and its construction using the patent data is unrelated with how the test portfolios are formed.

The U.S. patents are granted to both U.S. and non-U.S. originated inventions. We investigate whether the origins of technologies affect their pricing in U.S. stock returns. We separate all patents into two groups, U.S. and non-U.S., by the nationality of inventors and, using the aforementioned approach, construct the respective GPT factors as the difference between the average GPT patent growth and the average SPT patent growth in each group. We find that GPT risks from both U.S. and non-U.S. inventions are priced in U.S. stock returns, suggesting that "imported" technologies play an important role in the U.S. economy and stock market.

In the second part of our empirical analysis, we extend the scope of our study to international asset pricing and examine whether GPT risk is priced in global and regional stock portfolios constructed in Fama and French (2012) based on size and book-to-market sorts. During the sample period 1991-2006 of our international analyses, almost half of U.S. patents are granted to non-U.S. inventors. As already noted, the literature has commonly viewed U.S. patent data as representative of important inventions from all over the world. Following this view, we separate the patents in each technology category by the country of inventors, and form the global GPT factor and the regional GPT factors for Japan and Europe using the same approach defined earlier.

We find that the global GPT factor is significantly priced in the Fama-French global portfolios. When we replace the global factor by the U.S. and non-U.S. GPT factors, both factors are priced in global stock returns as well. Finally, we report an interesting contrast between Japanese and European stock returns: the U.S. GPT factor is more significantly priced than the Japanese GPT factor in the Fama-French Japanese portfolios, while the Europe factor, but not the U.S. factor, is significantly priced in the Fama-French European portfolios.

Taken together, our international analyses provide strong out-of-sample support to the evidence obtained from U.S. stock returns.[4] Since the U.S. GPT factor is priced in U.S. stock returns, the results suggest that in pricing technology risk, there is a higher degree of financial market integration between the U.S. and Japan than between the U.S. and Europe. Thus, our analyses contribute to a central question in international asset pricing on whether securities are priced globally in an integrated market or locally in segmented markets (Karolyi and Stulz 2003; Bekaert, Harvey, and Ng 2005; Bekaert, Harvey, Lundblad, and Siegel 2007). Moreover, our results suggest technology risk as a potential economic mechanism underlying market integration. This study also contributes to the literature on international technology diffusion by highlighting the systematic risk associated with cross-border technology spillovers in international stock markets.

Our study is complementary to but also distinct from existing studies in several dimensions: we focus on the role of GPTs and spillovers in cross-sectional asset pricing; we use patent data to measure GPT risk; we consider not only U.S. but also international stock portfolios; and our results point to asset pricing implications of innovation spillovers. Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001), and Laitner and Stolyarov (2003) propose a time-series relation between information technologies and aggregate stock market value. We focus on the cross-sectional variation of stock returns, i.e., how GPTs explain the returns from different stocks over the same period. Pastor and Veronesi (2009) and Garleanu, Stavros, and Yu (2012) develop and calibrate models to show that wide adoption of new technologies leads to systematic risks. We undertake an empirical approach to show that patent-

[4] Our paper is also related with the literature that uses international data to reexamine the cross-sectional stock return patterns originally documented in the U.S. and provides new insights based on country-specific characteristics (e.g., McLean, Pontiff, and Watanabe 2009, Hou, Karolyi, and Kho 2011, Fama and French 2012, and Watanabe, Xu, Yao, and Yu 2012, among others).

based measures of GPT risk are priced in stock portfolios. Kogan and Papanikolaou (2010) and Papanikolaou (2011) examine the differential effects of investment and consumption technologies on stock returns and construct a mimicking portfolio whose returns track investment-specific technology shocks. We focus on GPTs that influence all sectors and spill over to other countries, and our empirical GPT factor is based on technology information contained in patent data.

The rest of the paper is organized as follows. We discuss the theoretical motivation of GPT risk and our empirical methodology in Section 2. We describe the data in Section 3 and the construction of the GPT factor in Section 4. Section 5 presents the empirical results on the pricing of GPT risk in U.S. stock returns. Section 6 extends the analysis to global and regional portfolios. Section 7 concludes the paper.

2. Theoretical motivation and empirical methodology

The pervasive impact of GPTs on the macroeconomy suggests that GPT shocks are most likely non-diversifiable even if investors hold diversified portfolios of assets. In contrast, SPTs influence a narrower range of sectors and investors may be able to diversify away SPT shocks by holding stocks across different industries. The GPT shocks, therefore, represent a source of systematic risk. Asset pricing theory suggests that investors demand compensation for bearing GPT risk, and stocks with higher exposure to GPT risk earn higher expected returns. In this section, we discuss two asset pricing models that provide intuition for priced GPT risk. Then we present a linear factor model and discuss our estimation methodology.

2.1. Investment-based asset pricing

The investment-based asset pricing model of Cochrane (1996) suggests that the stochastic discount factor is a function of aggregate investment return. Since GPTs generate pervasive impacts on productive activities economy-wide, and a positive productivity shock implies an unexpectedly high investment return, shocks to GPTs drive aggregate productivity and investment return to vary over time, which, in turn, drives the pricing kernel.

The positive relation between GPTs and aggregate productivity is also consistent with a large literature in macroeconomics suggesting that technology changes drive aggregate productivity to vary over time. The real business cycle models, starting with Kydland and Prescott (1982) and Long and Plosser (1983), emphasize technology shocks in explaining business cycles. Prescott (1986) suggests that technology shocks explain more than half of the post-war U.S. economic fluctuations. More recently, Basu and Fernald (2002) and Basu, Fernald, and Kimball (2006) provide empirical evidence that pure technology growth has a significantly positive effect on aggregate productivity. Consistent with these studies, we find that our empirical GPT risk factor is positively correlated with contemporaneous U.S. industrial production growth, and positively predicts future U.S. industrial production growth rates.

Moreover, through channels such as research collaboration, human capital mobility, and foreign direct investment (Keller 2004), technologies developed and adopted in one economy spill over globally and can increase the R&D, the innovation output, and the productivity in other economies (Coe and Helpman 1995; Branstetter 2001; Keller 2002). As a result, when GPTs from one country transfer to another, they may give rise to priced systematic risk in foreign stock returns.

In summary, the investment-based asset pricing model suggests that GPT risk is priced in both U.S. and international stock markets.

2.2. Consumption-based asset pricing

In consumption-based models (e.g., Breeden 1979, Hansen and Singleton 1982, and Breeden, Gibbons, and Litzenberger 1989), the pricing kernel is a function of consumption growth. A number of existing studies provide economic intuition suggesting that aggregate consumption increases with GPTs. Campbell (1994) shows that persistent technological growth leads to higher consumption. The models of Pastor and Veronesi (2009) and Garleanu, Panageas, and Yu (2012) indicate that once a new technology is widely adopted, it improves both aggregate productivity and consumption. In addition, Greenwood, Hercowitz, and Krusell (1997) argue that technological development makes new equipment either less expensive or more efficient than old equipment, which improves productivity and increases consumption. These studies suggest that GPTs drive up consumption by raising aggregate productivity and market wealth.

More directly, Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001), and Jovanovic and Rousseau (2005) present empirical evidence showing that the success of the information technology revolution, owing to the introduction and the wide adoption of microprocessors, encourages consumption growth. We also find that the empirical GPT factor in our study is positively correlated with contemporaneous U.S. consumption growth. Further, the GPT factor predicts future U.S. consumption growth with positive slopes, suggesting that a positive shock to GPTs is associated with persistent consumption growth.[5]

Through technology spillovers, GPTs invented in one economy can increase the aggregate productivity and thus consumption in another economy. In addition, through international trade, consumption and equipment goods produced using advanced technologies in one economy can also increase consumption and wealth in other economies (Gong and Keller

[5] Given the predictive relation between the GPT factor and future consumption growth, our asset pricing results are consistent with the findings in Parker and Julliard (2005) that ultimate consumption risk, or consumption growth cumulated over 3 years, explains a large fraction of the cross section variation of stock returns.

2003; Keller 2004). Therefore, when GPTs from one country diffuse to another, they may become a source of priced risk in foreign stock markets.

In summary, the consumption-based asset pricing model also implies that GPT risk is priced in both U.S and international stock returns.

2.3. Linear GPT factor model

Motivated by the economic intuition discussed above, we empirically test if GPT risk is priced in the cross section of stock returns. We include an empirical GPT factor (more details on the construction of the factor are provided in Section 4) in a multi-factor model for excess returns:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{iGPT}\, GPT_t + \beta_{i1}\, F_{1,t} + ... + \beta_{iK}\, F_{K,t} + e_{i,t}\ .$$

Our tests use annual data, and following the standard practice in the literature to minimize estimation errors, we use stock portfolios instead of individual stocks in testing the model. Hence, $r_{i,t}$ is the return for stock portfolio i in year t, $r_{f,t}$ is the risk-free rate known at the beginning of year t, GPT_t is the GPT factor, $F_{1,t}$ to $F_{K,t}$ are other systematic risk factors, α_i is a constant, β_{iGPT} is the exposure (i.e., beta) of the excess return of asset i to the GPT factor, β_{i1} to β_{iK} are the exposures to the other factors, and $e_{i,t}$ is the residual. The model implies a relation between the expected excess return and the betas:

$$E[r_{i,t} - r_{f,t}] = \lambda_0 + \lambda_{GPT}\, \beta_{i,GPT} + \lambda_1\, \beta_{i1} + ... + \lambda_K\, \beta_{iK}\ ,$$

where λ_0 is the zero-beta rate, λ_{GPT} is the risk premium of the GPT factor to compensate the exposure to GPT risk, and λ_1 to λ_K are the risk premiums to compensate for other risks.

In estimating the model, we follow the standard two-stage cross-sectional regression approach. The first stage estimates betas (β_{iGPT} and β_{i1} to β_{iK}) as slope coefficients in the time-series regression of excess returns of each asset on factors over the entire sample period, while the second stage estimates factor risk premiums (λ_{GPT} and λ_1 to λ_K) as slope coefficients in cross-sectional regressions of average excess returns on betas across all portfolios. We use OLS in both stages,[6] and compute the standard errors of the estimated factor risk premiums using two methods. In the first method, following Fama and MacBeth (1973), in each time period we run a cross-sectional regression of realized excess returns on betas. By construction, the time-series averages of these slope coefficients are the same as the estimated factor risk premiums. The time-series standard errors of the average slope coefficients are used as the standard errors of the estimated factor risk premiums. In the second method, we follow Jagannathan and Wang (1998) and also incorporate Newey-West (1987) adjustment, and the resulting standard errors are robust to heteroskedasticity and time-series correlations in stock returns, and also account for the sampling errors in the betas estimated in the first stage.

To assess the model performance in fitting the cross section of stock returns, we report two goodness-of-fit measures. We compute the pricing error as the difference between the realized and the model-predicted average excess returns, and report the mean absolute pricing error (MAPE) as the average of the absolute values of the pricing errors across the portfolios. We also report the R^2 of the second-stage cross-sectional regression. For formal statistical inference, we report the F statistic suggested in Shanken (1985) and the associated p value on the

[6] As pointed out in Cochrane (2005, Chapter 12), while generalized least squares can potentially improve efficiency, OLS is more robust, especially when the cross section is large (i.e., there are many test portfolios).

null hypothesis that all pricing errors are jointly zero. This statistic accounts for the sampling errors in the betas estimated in the first stage as well as the small sample bias.

3. Data

We use the National Bureau of Economic Research (NBER) patent database, which covers the patents granted by the U.S. Patent and Trademark Office (USPTO) each year for the period of 1963-2006.[7] The construction of the database is documented in Hall, Jaffe, and Trajtenberg (2001).

The U.S. patents are granted to assignees (i.e., patent owners) both in the U.S. and from worldwide. Due to the territoriality principle, inventors who want to secure the business value of their inventions in the U.S. must file for U.S. patents. Since the U.S. boasts the largest economy and probably the highest demand for advanced technologies, inventors from other countries have strong incentives to file for U.S. patents. The U.S. patents as issued by the USPTO pursuant to common patent standards are also more homogenous in quality. As a result, the literature has commonly viewed U.S. patent data as representative of important inventions from all over the world (e.g., Griffith, Harrison, and Van Reenen 2006; Acharya and Subramanian 2009; Hsu, Tian, and Xu 2014). The country locations of patent assignees are reported in the database, allowing us to identify the origin of technology changes, and in particular, to measure GPT risk and conduct asset pricing tests for the international setting.

Based on the technology classes assigned by the USPTO, Hall, Jaffe, and Trajtenberg (2001) classify each patent into one of six major technological categories: (1) chemical, (2) computer and communications, (3) drugs and medical, (4) electrical and electronic, (5)

[7] The original database constructed by Hall, Jaffe and Trajtenberg for patents granted in the period 1963-1999 is available at http://www.nber.org/patents/, and the updated database for patents granted in the period 1976-2006 is available at https://sites.google.com/site/patentdataproject/Home.

mechanical, and (6) others. We define categories 2 and 4 as GPTs, and the remaining four categories — 1, 3, 5, and 6 — are SPTs. Our definition of GPTs follows the consensus in the literature. As noted in Greenwood and Jovanovic (1999), Brynjolfsson and Hitt (2000), Hobijn and Jovanovic (2001), and Jovanovic and Rousseau (2005), electricity is a major GPT since late 19th century, and over the past several decades, information technology is the most prominent example of GPTs. In additional analyses (Section 5.2), we also investigate the two categories separately and obtain similar empirical results.

For our baseline specification, we construct an empirical GPT factor using all the patents granted by the USPTO to both U.S. and non-U.S. inventors. We document the relation between this GPT factor and U.S. macroeconomic variables, and study the pricing of the factor in the U.S. stock market. The sample period is 1963-2006. The inclusion of the patents by non-U.S. inventors is motivated by the intuition that technologies invented outside the U.S. but patented in the U.S. also contribute to U.S. productivity growth and thus should impact the U.S. stock market. This is supported in Section 5.2, in which we separate patents by the country of assignees, construct the U.S. and non-U.S. GPT factors, and show that both factors are priced in U.S. stock returns. In Section 6, we further extend the analysis to the international setting. We separate patents by the country of inventors, construct the global and regional (i.e., Japanese and European) GPT factors, and study whether they are priced in global and regional stock portfolios.

For U.S. macroeconomic variables, consumption is per capita real expenditures on nondurable goods and services, and GDP is per capita real gross domestic product. Both are obtained from the Bureau of Economic Analysis. The U.S. industrial production index is from the Federal Reserve.

We obtain asset pricing data from Kenneth French's online data library.[8] We use Fama-French portfolios and factors based on size and book-to-market sorts, which are readily available for both the U.S. (Fama and French 1992) and the international setting (Fama and French 2012), and have been extensively used in asset pricing tests. Specifically, for the tests with U.S. stock returns, we use the Fama-French 25 portfolios sorted on size and the book-to-market ratio as the test portfolios and the Fama-French three factors (i.e., market excess return, the small-minus-big size spread, and the high-minus-low book-to-market spread) as common risk factors (Fama and French 1992 and 1993). For international asset pricing tests, we use the portfolios and factors formed on size and book-to-market constructed by Fama and French (2012) based on the accounting information and stock returns from 23 countries with developed stock markets. The data include the Fama-French 25 portfolios and the Fama-French factors for four regions — Europe, Japan, Asia Pacific excluding Japan, and North America — and the global portfolios and factors for all the 23 countries in the four regions combined.[9] All the returns and the factors are in U.S. dollars, and excess returns are obtained by subtracting the U.S. risk-free rates. Intersecting the sample period of the international asset pricing data with that of the patent database yields a sample period of 1991-2006. The time span limits the number of portfolios we can include in the cross section.[10] We select 9 of the 25 portfolios, formed as intersections of size quintiles 1, 2, and 5 and book-to-market quintiles 1, 3, and 5.[11] The inclusion of the extreme quintiles 1 and 5 well preserves the range of the average return variation across the 25 portfolios,

[8] The online data library is at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html .

[9] The European factors and portfolios cover Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The Asia Pacific factors and portfolios cover Australia, Hong Kong, New Zealand, and Singapore. The North American factors and portfolios cover Canada and the United states.

[10] If the number of portfolios N is greater than the number of time periods T, then at most T portfolios' returns are linearly independent, while the remaining portfolios' returns are redundant.

[11] Here "quintiles" are used in a loose sense. As discussed in Fama and French (2012), the size breakpoints for a region are the 3rd, 7th, 13th, and 25th percentiles of the region's aggregate market capitalization. The book-to-market breakpoints for all stocks in a region are the 20th, 40th, 60th, and 80th percentiles of the book-to-market ratio for the big (top 90% of market cap) stocks of the region. The global portfolios use global size breaks, but the book-to-market breakpoints for each region to allocate the region's stocks to the global portfolios.

and the selection of size quintile 2 and book-to-market quintile 3 helps achieve an evenly distributed coverage.

4. GPT factor

For each of the six technology categories, we use the number of patents granted (i.e., approved) every year as the measure of technology innovations in that category.[12] We use the grant year rather than the application year because GPT patents diffuse and become widely adopted in the whole economy mainly after their technical contents are disclosed to the public on their grant dates. We compute patent growth as the first difference of log number of patents in each category to measure the respective innovation growth.

Panel A of Table 1 presents key summary statistics for patent growth rates. The top three fastest growth rates are for categories 2, 3, and 4, which are generally viewed as high technologies. Both GPT categories are in the top three: patents in category 2, computer and communications, grow at 7.71% per year, which is the fastest among all six categories; patents in category 4, electrical and electronic, grow at 4.17% per year, which is the third fastest. The only SPT category whose patents grow fast is category 3, drugs and medical, with an average growth rate of 5.92% per year. The patent growth rates for categories 2, 3, and 4 are also more volatile. For the remaining three SPT categories, the average patent growth rates are below 2%, and the growth rate volatilities are also lower. Overall, GPT patent growth rates are higher and more volatile than SPT patent growth rates. Panel B of Table 1 shows that the six patent growth rates are all positively correlated. The correlation between the two GPT growth rates is 0.899. In

[12] Kamien and Schwartz (1975) review related literature and conclude that the number of patents granted serves as an appropriate proxy for innovation output. Although patents vary in their economic impacts and business values, we resort to the ‘‘law of large numbers’’ argument and treat all patents as random samples from one identical distribution (Scherer 1984 and Griliches 1990). Thus, using the total number of patents in each category every year is expected to average out idiosyncratic variations in individual patents.

addition, GPT patent growth rates are also correlated with SPT patent growth rates.

These empirical properties are consistent with two other defining characteristics of GPTs emphasized in the literature: potential for continued improvement and innovation complementarity (Bresnahan and Trajtenberg 1995). The fast growth of GPT patents signifies continued improvement. Innovation complementarity implies the spillover effects between GPTs and application technologies — GPTs enable innovations in other technologies, and vice versa. The large and positive correlations between GPT and SPT patent growth rates are consistent with such innovation spillovers. As a result, the GPT patent growth rates are not simply equated with non-diversifiable GPT risk, since the positive correlations imply that part of the variations in GPT patent growth rates are driven by diversifiable SPT shocks.

We propose an empirical proxy for non-diversifiable GPT shocks as the difference between the average of the two GPT patent growth rates and the average of the four SPT patent growth rates. Such a differencing approach also helps to remove the effects of any regulation changes in U.S. patent laws and institutional changes in the USPTO that most likely affect all patents. Fig. 1 presents the time series variation of the factor. As reported in Panel A of Table 2, the GPT factor has a mean of 3.47% and a volatility of 7.92%. In addition, the GPT factor is serially uncorrelated, with an insignificant autocorrelation coefficient of 0.06. Panel B of Table 2 reports the correlations between the GPT factor and the six patent growth rates. The correlations between the GPT factor and the two GPT patent growth rates are highly positive and significant — 0.567 with category 2 patent growth and 0.508 with category 4 patent growth. In contrast, the correlations between the GPT factor and the four SPT patent growth rates are small in magnitudes and insignificant. In other words, the GPT factor captures a large part of the variations in the GPT patent growth rates, but is almost orthogonal to the SPT patent growth rates. These results suggest that our GPT factor is most probably highly correlated with non-diversifiable GPT shocks but almost uncorrelated with diversifiable SPT shocks.

Panel A of Table 2 also displays the summary statistics for the Fama-French factors for the U.S. stock market and several U.S. macroeconomic variables. Over the sample period, the average risk premium for the aggregate U.S. stock market (MKT) is 6.35%, the size factor SMB has a mean of 3.88%, and the value factor HML has a mean of 6.32%. All return factors are very volatile. The U.S. nominal risk-free rate (Rf) is 5.81% over the sample period. Among the macroeconomic variables, consumption growth (ΔC) is 2.27% on average and appears to be smooth, with a standard deviation of only 1.16%; GDP growth (ΔGDP) is 2.24% on average, and its volatility is 1.97%; industrial production growth (ΔIP) is 3.00% on average, and its volatility is 4.00%.

Panel B of Table 2 also indicates that the GPT factor is positively correlated with all three Fama-French factors of U.S. stock returns. The correlation with HML is the largest and also highly significant. These positive correlations suggest the possibility that the Fama-French factors may capture non-diversifiable technology risk. The GPT factor is also positively correlated with U.S. consumption, GDP, and industrial production growth. While these correlations are not significant at conventional levels, the results suggest that the GPT factor varies pro-cyclically over time — it is high during good times, and low during bad times.

In Panel C of Table 2 we investigate whether the GPT factor exhibits any predictive power for future macroeconomic variables. The results show that the GPT factor forecasts the cumulative growth rates of consumption, GDP, and industrial production with positive slopes over horizons of 1 to 3 years. The statistical significance of the slopes, based on Newey-West (1987) standard errors, increases substantially with the horizon, and the results are strongly positive for horizons of 2 and 3 years. The magnitudes of the slopes and the R^2 values also increase with the horizon. These results are notable, in particular because the predictive variable, the GPT factor, is serially uncorrelated. More importantly, these results provide support to the theoretical motivation discussed in Section 2 for the pricing of GPT risk in asset returns.

5. GPT risk and U.S. stock returns

In this section we investigate whether the GPT factor is priced in U.S. stock returns. We also evaluate the contribution of the GPT factor in explaining the cross section of U.S. stock returns.

5.1. Fama-French 25 portfolios

We use the Fama-French 25 portfolios for the U.S. stock market, which are the intersections of 5 portfolios formed on size and 5 portfolios formed on the ratio of book equity to market equity. These portfolios exhibit a large dispersion in average returns and have been extensively used in asset pricing tests. They highlight the size effect — firms with small market capitalization have on average higher returns — and the value effect — firms with high book-to-market have on average higher returns. The results are reported in Table 3.

Column 1 estimates a model with the GPT factor as the single factor. The model delivers a remarkable performance — a single GPT factor can explain the cross section of average excess returns with an R^2 of 75.8% and an average pricing error of 1.37% per year. The estimated risk premium for the GPT factor is 14.8% per year, which is strongly significant. In addition, in the second-stage cross-sectional regression, the intercept is small and statistically insignificant. The large p value of 86.5% for the F statistic of 0.617 suggests that the null hypothesis of zero pricing errors is not rejected.

In Column 2, we include the market excess returns (MKT) as the second factor. In this two-factor model, the risk premium for the GPT factor rises slightly to 15.5% and remains highly significant. The risk premium estimated for the market factor is 8.2% but insignificant, consistent with Fama and French (1992). The two-factor model slightly improves the R^2 to 76.9% and lowers the average pricing error to 1.35%. The null hypothesis of zero pricing errors is again not rejected.

As comparison, we estimate in Column 3 the three-factor model of Fama and French (1993), which has been shown to perform well in explaining the returns of size and book-to-market sorted portfolios. The estimated risk premium is negative and insignificant for the market factor. For the size factor SMB, the risk premium is 3.9% and significant. For the value factor HML, the risk premium is 6.5% and highly significant. The Fama-French three-factor model attains a high R^2 of 82.7% and an average pricing error of 1.16%, although the intercept in the second stage regression is large and significant. The p value of 30.2% for the F test suggests that the null of zero pricing errors is not rejected.

To visualize the goodness of fit, Panel A of Fig. 2 plots the average realized excess returns of the Fama-French 25 portfolios with respect to those predicted by the single GPT factor model. Following the convention in the literature, we denote a portfolio by the rank of its size and then the rank of its book-to-market ratio. For example, portfolio 15 contains the smallest quintile of stocks by size and the largest quintile of stocks by book-to-market. If the model made perfect predictions, then all the points would lie on the 45 degree diagonal line. Confirming the R^2 of 75.8%, the points are located close to the 45 degree line. The three largest pricing errors occur with portfolios 42 (size quintile 4 and book-to-market quintile 2), 52, and 14. For comparison, Panel B of Fig. 2 plots the results obtained with the Fama-French three-factor model. The three largest pricing errors are for portfolios 51, 15, and 41.

Finally, we estimate a four-factor model that includes the GPT factor and the Fama-French three factors. The risk premium for the GPT factor reduces to 7.2% but remains significant. The risk premiums for the Fama-French three factors are largely unchanged. The R^2 increases to 86.1%, and the pricing error drops to 1.05%. Hence, the GPT factor contains additional information and contributes explanatory power above and beyond conventional return factors.

Overall, in explaining the average returns of the Fama-French 25 portfolios, the GPT factor performs comparably to the Fama-French three-factor model. In addition, the GPT factor remains significantly priced even after controlling for the Fama-French factors. The performance of the GPT factor is noteworthy in that it is derived from the patent data. In particular, unlike other return-based factors, the GPT factor is not related with the construction of the test portfolios. In unreported results, we also find that the GPT factor substantially outperforms the models using consumption growth or industrial production growth as factors.

To further understand the asset pricing performance of the GPT factor, Table 4 reports the average excess returns for the Fama-French 25 portfolios in Panel A and the betas from regressing the excess portfolio returns on the GPT factor in Panel B. Panel A confirms the value premium: in each size quintile, high book-to-market firms (i.e., value firms) earn higher returns than low book-to-market firms (i.e., growth firms). The betas in Panel B demonstrate a corresponding pattern — high book-to-market firms have higher betas than low book-to-market firms. Panel A also largely confirms the size effect — in all but the lowest book-to-market quintile (i.e., the extreme growth quintile), small firms earn higher returns than large firms. In

Panel B, small firms have higher betas than large firms. Overall, the betas are positively correlated with average excess returns, with a high correlation coefficient of 0.87.

5.2. Additional analyses

So far, in our baseline specification, the empirical GPT factor is the difference between the average of the two GPT (categories 2 and 4) patent growth rates and the average of the four SPT (categories 1, 3, 5 and 6) patent growth rates. In Panel A of Table 5, we investigate the robustness of the asset pricing results to alternative construction of the GPT factor. The test assets are the Fama-French 25 portfolios sorted on size and book-to-market for the U.S. stock market.

In line 1, we focus on category 2, computer and communications, as the GPT, and calculate the GPT factor as the difference between the growth of category 2 patents and the average SPT patent growth. The single GPT factor model achieves an R^2 of 63.2%, lower than that obtained by the GPT factor in the baseline specification. The estimated risk premium is 13.3%, slightly lower than that for the baseline GPT factor. In line 2, we focus on category 4, electrical and electronics, as the GPT, and calculate the GPT factor as the difference between the growth of category 4 patents and the average SPT patent growth. The resulting R^2 value of 65.5% is also lower than that obtained by the baseline GPT factor. The estimated risk premium is 16.2%, slightly higher than that for the baseline GPT factor. Overall, these results suggest that both GPT categories are important in order to achieve the best cross-sectional explanatory power.

Recent decades have also witnessed the fast growth of and the intensifying public attention on biotechnologies. To investigate whether biotechnologies have gained the GPT status in the context of the asset pricing tests, we construct a factor as the difference between the patent growth of category 3 (drugs and medical) patents and the average of the patent growth rates of categories 1, 5, and 6. Line 3 reports that the factor based on biotechnologies does a poor job in explaining the cross section of stock returns. In addition, the estimated factor risk premium is essentially 0.

The baseline GPT factor is constructed using all patents in the database, which include both U.S. and non-U.S. inventions. During the first few years of the 1963-2006 sample period, the patents granted to non-U.S. inventors make up about 20% of all the granted patents each year. By early 1980s, the fraction of U.S. patents granted to non-U.S. inventors each year has increased to about 45%, and remains around this level through the end of the sample period. Altogether, during 1963-2006, about 42% of U.S. patents are granted to non-U.S. inventors.

The inclusion of non-U.S. inventions in the GPT factor is motivated by the intuition that technologies invented outside the U.S. but patented in the U.S. also contribute to U.S. productivity growth and impact the financial markets. This appears reasonable from the perspective of patent applicants — the fact that foreign inventors seek U.S. patent protection suggests that they expect their intellectual property to be valuable to users of technologies in U.S. economy. Furthermore, given the substantial fraction of non-U.S. inventions included in the U.S. patent database and thus incorporated in the construction of the GPT factor, the asset pricing performance reported thus far suggests that GPT risk due to non-U.S. inventions is most probably priced in the U.S. stock market.

To provide further confirmation, we separate the patents in each technology category by the country of assignees. Using only the patents granted to U.S. inventors, we construct a U.S. GPT factor as the difference between the average GPT and SPT patent growth rates. Using only the patents granted to non-U.S. inventors, we construct a non-U.S. GPT factor. These two factors represent GPT risks originated from U.S. and non-U.S. inventions, respectively. In unreported tables, we find that the two GPT factors are positively correlated, with a correlation of 0.70. Both factors are positively correlated with the Fama-French U.S. factors, and the correlations are higher for the U.S. GPT factor. Both factors predict future growth rates of U.S. consumption, GDP, and industrial production, and the results are stronger for the U.S. GPT factor.

Panel B of Table 5 reports the asset pricing results for a two-factor model with U.S. and non-U.S. GPT factors, and the test assets are the Fama-French 25 portfolios for the U.S. stock market. Both factors are significantly priced, and the estimated factor risk premiums are similar to that for the GPT factor constructed using all the patents. The two-factor model achieves an R^2 of 78.3%, higher than that obtained by the GPT factor constructed using all the patents. The null hypothesis of zero pricing errors is not rejected.

Altogether, these findings — foreign technologies predict U.S. macroeconomic variables and are priced in U.S. stock returns — provide direct validation for the inclusion of non-U.S. inventions in the baseline GPT factor. The results also suggest that technology spillovers are priced by investors in the U.S. stock market.

6. GPT risk and international stock returns

In this section, we turn to the international setting and study the pricing of GPT risk in the global stock portfolios and the regional stock portfolios of Japan and Europe. This is a natural extension of the previous investigation, which finds that GPT risk originated from non-U.S. inventions is priced in U.S. stock returns. There are two additional motivations for the investigation. First, international asset pricing results are out-of-sample tests on the robustness of the results obtained using U.S. stock portfolios. Second, and perhaps more importantly, our international results contribute to a central question in the international asset pricing literature on whether securities are priced locally in segmented markets or globally in an integrated market (Karolyi and Stulz 2003; Bekaert, Harvey, and Ng 2005; Bekaert, Harvey, Lundblad, and Siegel 2007). The extant empirical evidence appears to support an intermediate case between the polar extreme of full integration or full segmentation. Most studies addressing the question use factors based on returns and firm characteristics. Our analysis using patent-based factors highlights technology spillovers and innovation complementarities across borders as potential economic mechanisms driving market integration and systematic risk.

As described in Section 3, the international asset pricing data are the global and regional Fama-French portfolios and factors formed on size and book-to-market (Fama and French 2012). The sample period is 1991-2006, and for test assets, we select 9 out of 25 portfolios, formed as intersections of size quintiles 1, 2, and 5 and book-to-market quintiles 1, 3, and 5.

Panel A of Table 6 reports the average fractions of the patents by the region of assignees during the period 1991-2006. We follow the definition of the four regions in the asset pricing data, except that we split North America into the U.S. and Canada. The results show that U.S. originated patents account for about 53.5% of all patents granted by the USPTO. This suggests that almost half of patents granted in the U.S. are "imported" inventions. Specifically, about 21.2% of the patents are granted to Japanese assignees, about 16.9% to European assignees, and inventors from the rest of the world claim the remaining 8.4%.

Using the U.S. patent database, we form regional and global GPT factors, corresponding to the regional and global portfolios and factors. Specifically, for each region, using only the patents granted to inventors in that region, we form the regional GPT factor as the difference between the average GPT growth rates and the average SPT growth rates. We combine the patents granted to assignees of all the 23 countries, and form the global GPT factor.[13]

We investigate whether these GPT factors are priced in the global and regional stock portfolios. Among the four regions, we focus on Japan and Europe for their prominent presence in the U.S. patent database. The Asia Pacific region defined in the asset pricing data, which covers the four developed stock markets (Hong Kong, Singapore, Australia, and New Zealand), appears not representative of the technological developments in that region: these four economies claim less than 1% of the U.S. patents, while Taiwan and South Korea claim 4.2%. The North America region contains only the U.S. and Canada, but Canada only holds 2.1% of the U.S. patents.

Panels B and C in Table 6 report key summary statistics of the regional and global GPT factors. All GPT factors are positively correlated with each other. The correlations between the GPT factors of non-overlapping regions, such as the U.S., Japan, and Europe, are consistent with technology spillovers and innovation complementarities across borders. In particular, the correlation between the U.S. and Japanese GPT factors is 0.794, higher than the correlation of 0.697 between the U.S. and European factors.

6.1. Global stock portfolios

Table 7 reports the asset pricing results with the Fama-French global portfolios. Columns 1 and 2 show that the global GPT factor is significantly priced, with and without the global market factor. When the global GPT factor is the only factor, it explains 49.7% of the cross-

[13] The global GPT factor is slightly different from the baseline GPT factor constructed in Section 3, which is used for the U.S. stock portfolios in Section 4. Here, the global GPT factor is based on the patents granted to inventors in the 23 countries, which, according to Panel A of Table 6, hold about 95% of the U.S. patents. The baseline GPT factor is constructed using all the patents granted by the USPTO. As can be expected, the two factors are highly correlated: the correlation is 0.993 during 1991-2006.

sectional variation of stock returns. The R^2 achieved by the two-factor model with the global GPT and market factors is 69.6%, higher than the R^2 of 64.1% reported in Column 5 by the Fama-French global three-factor model. To visualize the goodness-of-fit, Fig. 3 plots the realized average excess returns with respect to those predicted by the single global GPT factor model, as compared with the plot for the Fama-French global three-factor model.

To further understand the pricing of GPT risk in global portfolios, we replace the global GPT factor by the U.S. and non-U.S. GPT factors. Columns 3 and 4 of Table 7 suggest that both factors are priced. The statistical significance is stronger for the non-U.S. factor. Thus, inventions generated in and outside of the U.S. are both relevant for global stock returns. This finding also complements the result reported in Section 5.2 that both the U.S. and non-U.S. factors are priced in the U.S. stock market.

The results from different models point to similar estimates between 5% and 7% per year for the risk premiums of the GPT factors. The intercepts are insignificant, and the lowest R^2 is about 50%. Thus, a substantial fraction of the cross-sectional variation of global stock returns is accounted for by the GPT factors, and both the U.S. and non-U.S. innovations are important in global asset pricing. The results support integrated financial markets among developed countries, and suggest that a potential channel for integrated pricing of stocks is technology risk driving common variations in global stock returns. The results also support the common view held by the literature that the U.S. patent database captures important inventions from worldwide. Furthermore, the results provide out-of-sample support for the results using the U.S. stock portfolios.

6.2. Regional stock portfolios

We then study the pricing of GPT risk in two regional portfolios – those of Japan and Europe. Besides regional GPTs, we also include the U.S. GPT factor so as to test whether financial markets are integrated in pricing technology risk. The results are presented in Table 8.

We first study the pricing of GPT risk in the Fama-French portfolios of Japanese stocks. A model with the single Japanese GPT factor can explain about 56.8% of the cross-sectional variation of average excess stock returns, and the estimated GPT factor risk premium is 4.8%. Further including the U.S. GPT factor improves the R^2 to 60.9%. The estimated risk premium is 4.2% for the U.S. GPT factor. The risk premium for the Japanese GPT factor lowers to 4.1%, and the statistical significance is weaker than that for the U.S. GPT factor. In both models, the intercepts in the second-stage regressions are insignificant. As comparison, the model using the Fama-French Japanese three factors achieves an R^2 of 93.0%, and the intercept is significantly negative. The goodness-of-fit plots for the single Japanese GPT factor and the Fama-French three-factor model are presented in Fig. 4.

Overall, both local and U.S. GPT risks are priced in Japanese stock returns. Section 5 has already reported that the U.S. GPT factor is priced in U.S. stock returns. Together, these results corroborate a considerable degree of the financial market integration between the U.S. and Japan in pricing technology risk. This is perhaps not surprising — over the sample period of 1991-2006, the U.S. and Japan are the top two largest economies in the world, with enormous flows of both goods and capital between these two countries. Japan is also one of the most innovative countries, as evidenced in its holding of 21.2% of U.S. patents.

Table 8 also reports the pricing of GPT risk in the Fama-French portfolios of European stocks. The model with the single European GPT factor achieves an R^2 of 77.2%. The European GPT factor risk premium is 8.1% with statistical significance. When we further include the U.S.

GPT factor, the R^2 increases to 87.4%. The European GPT factor remains significantly priced and the risk premium drops slightly to 7.8%. The U.S. GPT factor carries a small risk premium of 1.5%, which is statistically insignificant. As comparison, an R^2 of 91.6% is obtained by the Fama-French European three-factor model. The goodness-of-fit plots for the single European GPT factor and the Fama-French three-factor model are presented in Fig. 5.

Hence, unlike in Japan, European stock markets are more affected by locally originated technology risk than that from the U.S. During the sample period, four of the 13 European countries — Germany, France, UK, and Italy — are ranked among the top 10 economies by GDP, and as a whole, the European region forms a larger economy than Japan. However, the European countries hold 16.9% of the U.S. patents, about 80% of those granted to Japan. In addition, as noted earlier, the correlation between the U.S. and European GPT factors (which is 0.697) is lower than that between the U.S. and Japanese GPT factors (which is 0.794). In terms of pricing technology risk, the European stock markets appear to be less integrated with the U.S. stock market.

7. Concluding remarks

In this paper we propose that, due to their pervasive impacts on the macroeconomy, GPTs are a plausible source of non-diversifiable, systematic risk. We construct an empirical GPT factor using U.S. patent data, and find that the GPT factor is positively related with an array of pro-cyclical U.S. macroeconomic variables and U.S. return-based factors. We report significant and robust results showing that the GPT factor is priced with a risk premium of about 15% per year in the cross section of U.S. stock returns.

We then extend the analysis to global and regional portfolios and find that GPT risk is also significantly priced in international stock portfolios. The U.S. GPT factor helps explain the cross-sectional variations in global and Japanese stock portfolios, suggesting technology risk as a potential economic mechanism driving financial market integration. In addition, the finding that the non-U.S. GPT factor is priced in the U.S. and the U.S. GPT factor is priced in Japan provides evidence for technology spillovers from a financial markets perspective.

As in prior studies (e.g., Cochrane 1996; Lettau and Ludvigson 2001; Bansal, Dittmar, and Lundblad 2005, among others), we test the existence of a particular type of macroeconomic risk, and do not have any prior on individual test assets' factor exposure. Our findings suggest that, compared to large and growth stocks, exposure to GPT risk is higher for small and value stocks. This pattern of GPT betas provides a potential explanation for the size and the value effects, and also raises an interesting question on how this pattern arises from firms' investment and production processes. This exploration is beyond of the scope of the current paper and merits a separate study in the future.

Overall, our paper adds to the growing literature on GPTs and investment-based asset pricing, and highlights the role of global and regional technology risks in the cross section of stock returns.

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Table 1. Patent growth of six technology categories

For each technology category, patent growth is the annual log growth rate of the number of granted patents classified into that category. Panel A reports the means and the standard deviations. Panel B reports the correlations. The sample period is 1963-2006 for the number of patents, and thus 1964-2006 for patent growth.

A. Descriptive statistics

	Category	Mean (%)	Std Dev (%)
1	Chemical	1.44	12.71
2	Computer and communications	7.71	14.26
3	Drugs and medical	5.92	14.08
4	Electrical and electronic	4.17	13.26
5	Mechanical	1.59	11.85
6	Other	0.92	11.88

B. Correlations

Category	2	3	4	5	6
1	0.582	0.697	0.602	0.683	0.700
2		0.589	0.899	0.807	0.768
3			0.546	0.613	0.683
4				0.887	0.860
5					0.923

Table 2. GPT factor and U.S. macroeconomic variables and return factors

The general purpose technology (GPT) factor is the difference between the average of the two GPT patent growth rates and the average of the four specific purpose technology (SPT) patent growth rates. The two GPT patent categories are category 2, computer and communications, and category 4, electrical and electronic. The four SPT patent categories are category 1, chemical, category 3, drugs and medical, category 5, mechanical, and category 6, others. For each category, patent growth is the annual log growth rate of the number of granted patents classified into that category. MKT, SMB, and HML are annual Fama-French factors of U.S. stock returns. U.S. consumption growth, ΔC, is the annual log growth rate of per capita real expenditures on nondurables and services. U.S. GDP growth, ΔGDP, is the annual log growth rate of per capita real gross domestic product. U.S. industrial production growth, ΔIP, is the annual log growth rate of industrial production index. Rf is the U.S. annual nominal risk-free rate. The sample period is 1963-2006.

Panel A reports the means and the standard deviations of the variables. Panel B reports the correlations between the GTP factor and other variables. Panel C reports the slope coefficients and the R^2 values of the predictive regressions of cumulative growth rates of Y on the GPT factor,

$$Y_{t+1} + ... + Y_{t+h} = a_h + b_h \, GPT_t + e_{t+h} \, ,$$

where h = 1, 2, 3 is the horizon in years, and Y is consumption growth, GDP growth, or industrial production growth. The estimates are obtained with GMM. Standard errors, reported in parentheses, are Newey-West (1987) adjusted with 5 lags.

A. Descriptive statistics

	Mean (%)	Std Dev (%)
GPT factor	3.47	7.92
MKT	6.35	17.29
SMB	3.88	14.88
HML	6.32	14.21
Rf	5.81	2.77
ΔC	2.27	1.16
ΔGDP	2.24	1.97
ΔIP	3.00	4.00

B. Correlations

	Patent growth of technology categories					
	1	2	3	4	5	6
GPT factor	-0.202	0.567	-0.223	0.508	0.202	0.107
	(0.159)	(0.098)	(0.120)	(0.139)	(0.173)	(0.171)

	MKT	SMB	HML	ΔC	ΔGDP	ΔIP
GPT factor	0.189	0.051	0.261	0.130	0.046	0.039
	(0.174)	(0.156)	(0.103)	(0.133)	(0.183)	(0.171)

C. Predictive regressions by GPT factor

Horizon		ΔC	ΔGDP	ΔIP
1	Coeff	0.016	0.048	0.110
	Std Err	(0.025)	(0.037)	(0.075)
	R^2	0.012	0.037	0.047
2	Coeff	0.040	0.117	0.192
	Std Err	(0.027)	(0.050)	(0.093)
	R^2	0.030	0.092	0.061
3	Coeff	0.062	0.177	0.318
	Std Err	(0.037)	(0.053)	(0.095)
	R^2	0.042	0.146	0.124

Table 3. Two-stage cross-sectional regressions with the Fama-French U.S. 25 portfolios

The test assets are the Fama-French U.S. 25 portfolios formed on size and book-to-market. GPT is the empirical GPT factor, and MKT, SMB, and HML are the Fama-French factors for the U.S. stock market. The sample period is 1963-2006.

Each column reports the slope coefficients, the intercept, and the R^2 obtained from the second stage of the two-stage cross-sectional regressions. Standard errors are reported in parentheses: those in the first row are obtained with the Fama-MacBeth method, while those in the second row follow Jagannathan and Wang (1998) and also incorporate Newey-West (1987) adjustment with 5 lags. Pricing error is the difference between the realized and the model-predicted average excess returns. The mean absolute pricing error, MAPE, is the average of the absolute pricing errors across all test portfolios. F and p value are the F statistic (Shanken 1985) and the associated p value on the null hypothesis that the pricing errors are jointly zero.

	1	2	3	4
	0.148	0.155		0.072
GPT	(0.040)	(0.044)		(0.022)
	(0.056)	(0.061)		(0.036)
		0.082	-0.039	-0.024
MKT		(0.068)	(0.053)	(0.052)
		(0.137)	(0.042)	(0.065)
			0.039	0.035
SMB			(0.023)	(0.023)
			(0.027)	(0.026)
			0.065	0.069
HML			(0.022)	(0.022)
			(0.012)	(0.015)
	0.021	-0.002	0.098	0.088
Const	(0.035)	(0.057)	(0.045)	(0.045)
	(0.081)	(0.125)	(0.051)	(0.076)
R^2	0.758	0.769	0.827	0.861
MAPE (%)	1.37	1.35	1.16	1.05
F	0.617	0.683	1.271	0.925
p-value	0.865	0.806	0.302	0.569

Table 4. Average excess returns of the Fama-French U.S. 25 portfolios and betas on the GPT factor

Panel A reports the average excess returns of the Fama-French U.S 25 portfolios formed on size and book-to-market. Panel B reports the betas obtained by regressing the portfolio excess returns on the GPT factor in time series. The sample period is 1963-2006.

A. Average excess returns (%)

	Low	2	3	4	High
Small	5.48	11.67	12.47	15.26	17.30
2	5.45	9.02	12.59	13.77	14.53
3	5.38	9.79	9.83	12.18	14.63
4	6.79	6.79	9.94	12.11	11.99
Big	5.71	6.27	6.28	7.85	8.49

B. GPT factor betas

	Low	2	3	4	High
Small	0.289	0.604	0.712	0.681	0.987
2	0.233	0.376	0.586	0.646	0.792
3	0.223	0.486	0.505	0.713	0.731
4	0.208	0.551	0.691	0.827	0.515
Big	0.226	0.507	0.323	0.477	0.586

Table 5. Further analyses

The test assets are the Fama-French U.S. 25 portfolios formed on size and book-to-market. The sample period is 1963-2006.

Each line in Panel A reports the GPT factor risk premium and the R^2 obtained from the second stage of the two-stage cross-sectional regressions. Standard errors are reported in parentheses: those in the first row are obtained with the Fama-MacBeth method, while those in the second row follow Jagannathan and Wang (1998) and also incorporate Newey-West (1987) adjustment with 5 lags. The GPT factor is: in line 1, the difference between the patent growth of category 2 and the average patent growth of categories 1, 3, 5, and 6; in line 2, the difference between the patent growth of category 4 and the average patent growth of categories 1, 3, 5, and 6; in line 3, the difference between the patent growth of category 3 and the average patent growth of categories 1, 5, and 6.

Panel B reports the slope coefficients, the intercept, and the R^2 obtained from the second stage of the two-stage cross-sectional regressions. The U.S. GPT factor is constructed using only the patents granted to U.S. assignees. The non-U.S. GPT factor is constructed using only the patents granted to non-U.S. assignees. Standard errors are reported in parentheses: those in the first row are obtained with the Fama-MacBeth method, while those in the second row follow Jagannathan and Wang (1998) and also incorporate Newey-West (1987) adjustment with 5 lags. Pricing error is the difference between the realized and the model-predicted average excess returns. The mean absolute pricing error, MAPE, is the average of the absolute pricing errors across all test portfolios. F and p value are the F statistic (Shanken 1985) and the associated p value on the null hypothesis that the pricing errors are jointly zero.

A. Performance of alternative GPT factors

	GPT categories	SPT categories	Risk premium	R^2
1	2	1,3,5,6	0.133 (0.042) (0.062)	0.632
2	4	1,3,5,6	0.162 (0.048) (0.066)	0.655
3	3	1,5,6	0.007 (0.051) (0.052)	0.002

B. Two-stage cross-sectional regression with U.S. and non-U.S. GPT factors

	0.156
Non-U.S.	(0.043)
GPT	(0.065)
	0.151
U.S. GPT	(0.040)
	(0.058)
	0.019
Const	(0.030)
	(0.084)
R^2	0.783
MAPE (%)	1.30
F	0.623
p-value	0.857

Table 6. Descriptive statistics of international variables

Panel A reports the time-series averages of the percentages of the patents granted to assignees in various regions. Panel B reports the means and the standard deviations of the various GPT factors. For each region, the regional GPT factor is constructed using only the patents granted to assignees in that region. The global GPT factor is constructed using the patents granted to assignees in all the 23 countries included in forming global stock portfolios. Panel C reports the correlations between the various GPT factors. The sample period is 1991-2006 for the number of patents, and thus 1992-2006 for patent growth.

A. Percentage of patents assigned to various regions (%)

U.S.	Japan	Europe	Canada	Asia Pacific (ex Japan)	Other
53.5	21.2	16.9	2.1	0.8	5.5

B. Descriptive statistics

GPT factor	Mean (%)	Std Dev (%)
Global	6.29	5.77
U.S.	6.40	5.94
Non-U.S.	6.30	6.47
Japan	6.23	5.79
Europe	7.32	8.65

C. Correlations between GPT factors

	U.S.	Non-U.S.	Japan	Europe
Global	0.946	0.934	0.923	0.843
U.S.		0.770	0.794	0.697
Non-U.S.			0.953	0.895
Japan				0.777

Table 7. Two-stage cross-sectional regressions with the Fama-French global portfolios

The test assets are 9 of the Fama-French global 25 portfolios formed on size and book-to-market, selected as intersections of size quintiles 1, 2, and 5 and book-to-market quintiles 1, 3, and 5. For each region, the regional GPT factor is constructed using only the patents granted to assignees in that region. The global GPT factor is constructed using the patents granted to assignees in all the 23 countries included in forming global stock portfolios. Global MKT, SMB, and HML are the Fama-French factors for the global stock market. The sample period is 1991-2006.

Each column reports the slope coefficients, the intercept, and the R^2 obtained from the second stage of the two-stage cross-sectional regressions. Standard errors are reported in parentheses: those in the first row are obtained with the Fama-MacBeth method, while those in the second row follow Jagannathan and Wang (1998) and also incorporate Newey-West (1987) adjustment with 2 lags. Pricing error is the difference between the realized and the model-predicted average excess returns. The mean absolute pricing error, MAPE, is the average of the absolute pricing errors across all test portfolios. F and p value are the F statistic (Shanken 1985) and the associated p value on the null hypothesis that the pricing errors are jointly zero.

	1	2	3	4	5
Global GPT	0.066	0.061			
	(0.033)	(0.033)			
	(0.029)	(0.023)			
Non-U.S. GPT			0.068	0.065	
			(0.034)	(0.034)	
			(0.037)	(0.029)	
U.S. GPT			0.052	0.053	
			(0.032)	(0.030)	
			(0.029)	(0.040)	
Global MKT		-0.005		-0.010	-0.040
		(0.065)		(0.059)	(0.052)
		(0.024)		(0.033)	(0.057)
Global SMB					0.031
					(0.025)
					(0.029)
Global HML					0.065
					(0.039)
					(0.039)
Const	0.010	0.076	0.045	0.079	0.109
	(0.053)	(0.049)	(0.036)	(0.040)	(0.030)
	(0.072)	(0.077)	(0.049)	(0.075)	(0.032)
R^2	0.497	0.696	0.527	0.698	0.641
MAPE (%)	2.48	2.09	2.46	2.06	2.25
F	3.169	3.799	3.986	5.172	11.075
p-value	0.076	0.052	0.047	0.026	0.003

Table 8. Two-stage cross-sectional regressions with the Fama-French regional portfolios

For each region, the test assets are 9 of the Fama-French regional 25 portfolios formed on size and book-to-market, selected as intersections of size quintiles 1, 2, and 5 and book-to-market quintiles 1, 3, and 5. For each region, the regional GPT factor is constructed using only the patents granted to assignees in that region. Regional MKT, SMB, and HML are the Fama-French factors for regional stock markets. The sample period is 1991-2006.

Each column reports the slope coefficients, the intercept, and the R^2 obtained from the second stage of the two-stage cross-sectional regressions. Standard errors are reported in parentheses: those in the first row are obtained with the Fama-MacBeth method, while those in the second row follow Jagannathan and Wang (1998) and also incorporate Newey-West (1987) adjustment with 2 lags. Pricing error is the difference between the realized and the model-predicted average excess returns. The mean absolute pricing error, MAPE, is the average of the absolute pricing errors across all test portfolios. F and p value are the F statistic (Shanken 1985) and the associated p value on the null hypothesis that the pricing errors are jointly zero.

Region	Japan			Europe		
Regional GPT	0.048	0.041		0.081	0.078	
	(0.038)	(0.045)		(0.040)	(0.039)	
	(0.022)	(0.029)		(0.041)	(0.032)	
U.S. GPT		0.042			0.015	
		(0.031)			(0.026)	
		(0.023)			(0.020)	
Regional MKT			0.160			0.139
			(0.098)			(0.093)
			(0.064)			(0.096)
Regional SMB			0.011			0.002
			(0.031)			(0.026)
			(0.035)			(0.025)
Regional HML			0.031			0.083
			(0.054)			(0.036)
			(0.043)			(0.037)
Const	-0.061	-0.054	-0.138	0.054	0.119	-0.063
	(0.063)	(0.075)	(0.060)	(0.055)	(0.053)	(0.080)
	(0.060)	(0.051)	(0.075)	(0.044)	(0.076)	(0.137)
R^2	0.568	0.609	0.930	0.772	0.874	0.916
MAPE (%)	1.74	1.69	0.72	1.83	1.22	1.03
F	1.265	1.579	0.255	2.187	2.366	2.155
p-value	0.382	0.281	0.924	0.162	0.142	0.172

Fig. 1. GPT factor

The general purpose technology (GPT) factor is the difference between the average of the two GPT patent growth rates and the average of the four specific purpose technology (SPT) patent growth rates. The two GPT patent categories are category 2, computer and communications, and category 4, electrical and electronic. The four SPT patent categories are category 1, chemical, category 3, drugs and medical, category 5, mechanical, and category 6, others. For each category, patent growth is the annual log growth rate of the number of granted patents classified into that category. The sample period is 1963-2006 for the number of patents, and thus 1964-2006 for patent growth.

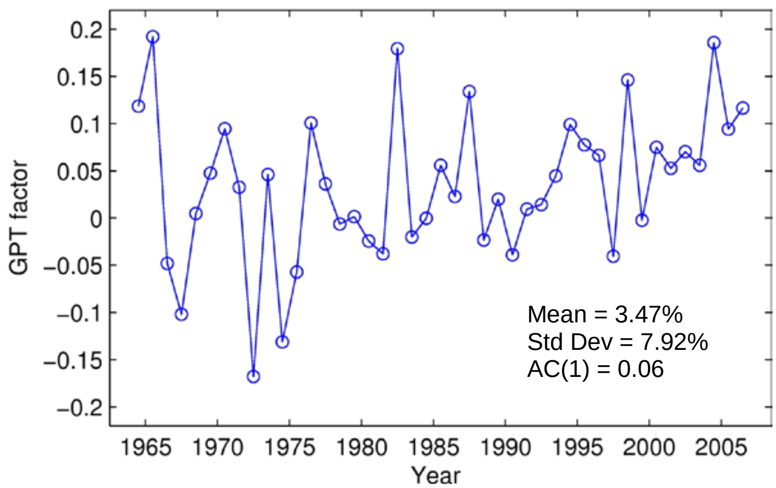

Fig. 2. Realized and model-predicted average excess returns for the Fama-French U.S. 25 portfolios

In Panel A the model includes only the GPT factor. In Panel B the model includes only the Fama-French three factors for the U.S. stock market. Each two-digit number represents a portfolio. The first digit is the size quintile (1 being the smallest and 5 being the largest), and the second digit is the book-to-market quintile (1 being the lowest and 5 being the highest). The sample period is 1963-2006.

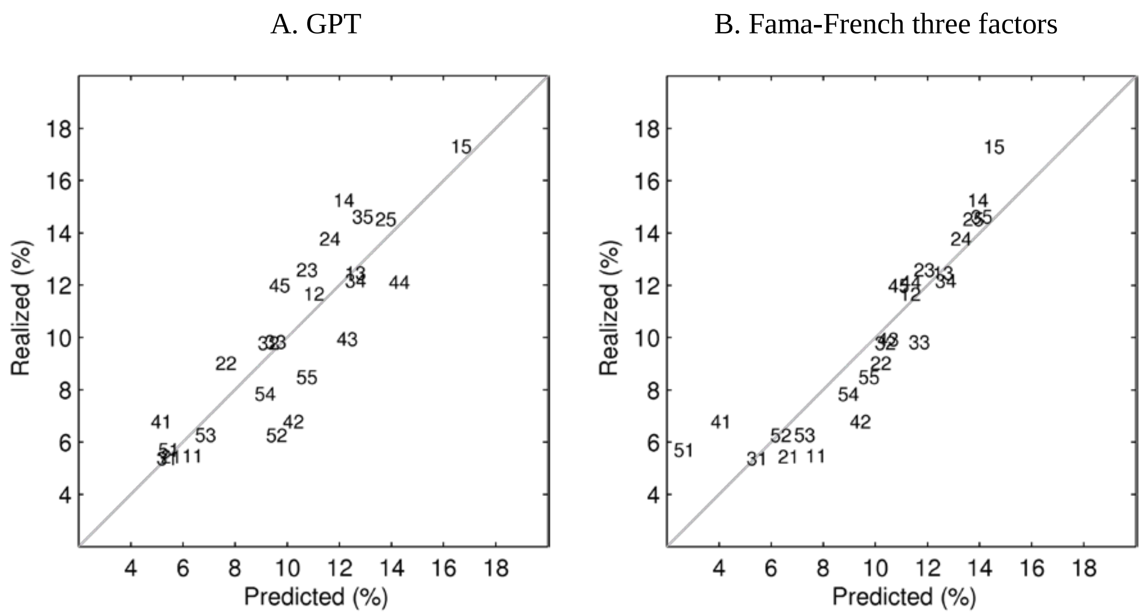

Fig. 3. Realized and model-predicted average excess returns for the Fama-French global portfolios

The test assets are 9 of the Fama-French global 25 portfolios formed on size and book-to-market, selected as intersections of size quintiles 1, 2, and 5 and book-to-market quintiles 1, 3, and 5. In Panel A the model includes only the global GPT factor. In Panel B the model includes only the Fama-French global three factors. Each two-digit number represents a portfolio. The first digit is the size quintile (1 being the smallest and 5 being the largest), and the second digit is the book-to-market quintile (1 being the lowest and 5 being the highest). The sample period is 1991-2006.

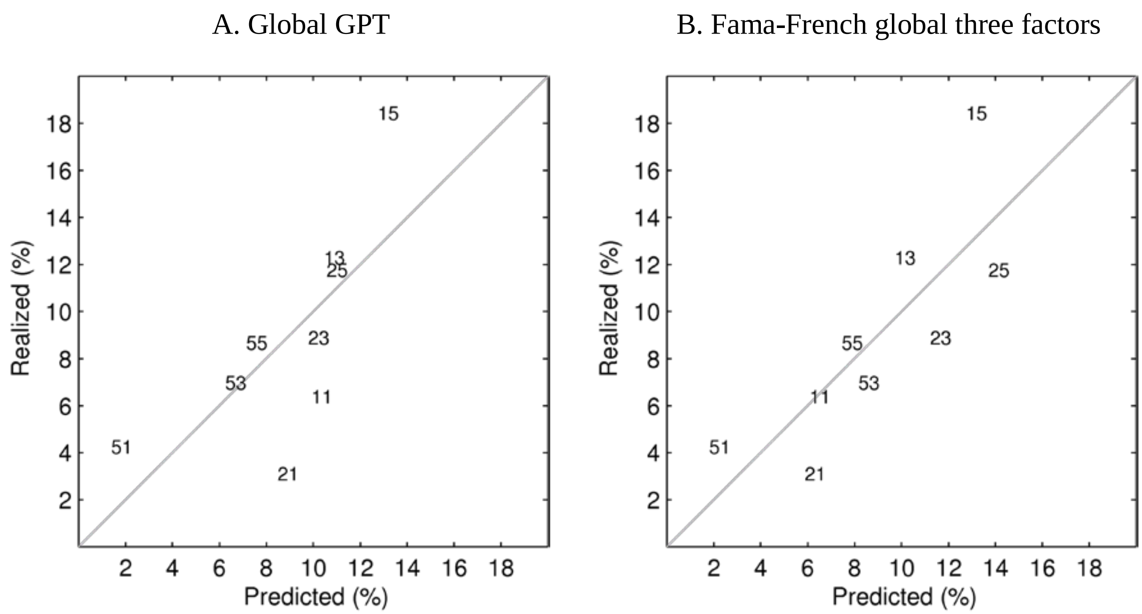

Fig. 4. Realized and model-predicted average excess returns for the Fama-French Japanese portfolios

The test assets are 9 of the Fama-French Japanese 25 portfolios formed on size and book-to-market, selected as intersections of size quintiles 1, 2, and 5 and book-to-market quintiles 1, 3, and 5. In Panel A the model includes only the Japanese GPT factor. In Panel B the model includes only the Fama-French Japanese three factors. Each two-digit number represents a portfolio. The first digit is the size quintile (1 being the smallest and 5 being the largest), and the second digit is the book-to-market quintile (1 being the lowest and 5 being the highest). The sample period is 1991-2006.

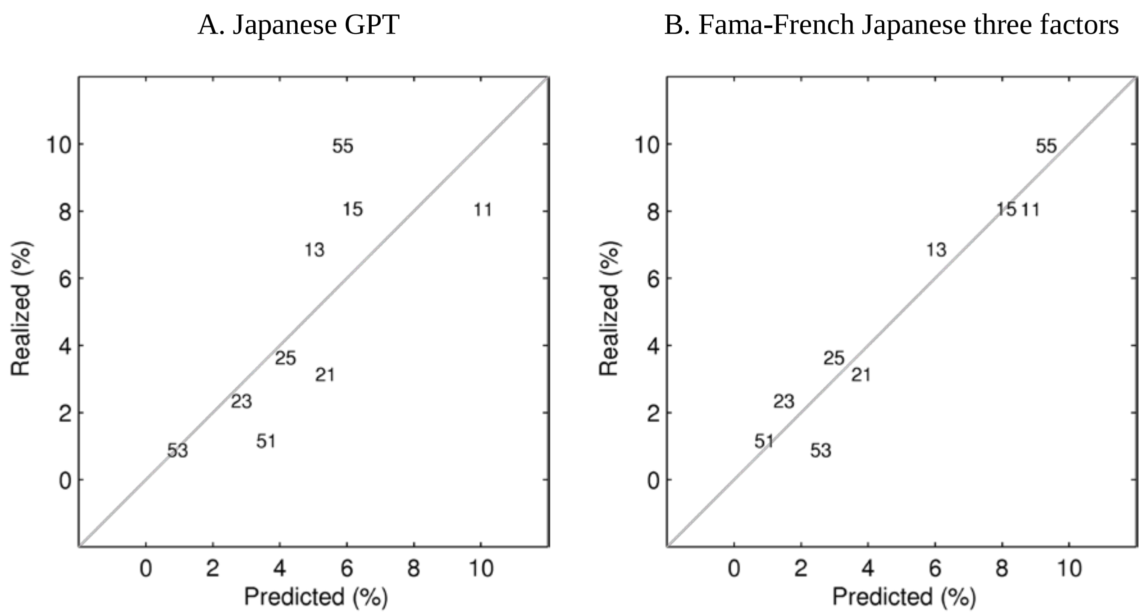

Fig. 5. Realized and model-predicted average excess returns for the Fama-French European portfolios

The test assets are 9 of the Fama-French European 25 portfolios formed on size and book-to-market, selected as intersections of size quintiles 1, 2, and 5 and book-to-market quintiles 1, 3, and 5. In Panel A the model includes only the European GPT factor. In Panel B the model includes only the Fama-French European three factors. Each two-digit number represents a portfolio. The first digit is the size quintile (1 being the smallest and 5 being the largest), and the second digit is the book-to-market quintile (1 being the lowest and 5 being the highest). The sample period is 1991-2006.

A. European GPT B. Fama-French European three factors