# Technological Diffusion, Uncertainty and Irreversibility: The International Diffusion of Industrial Robots[*]

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Abstract

The impact of uncertainty on the diffusion of new technology is explored. A probit type model of technological diffusion based upon a model of irreversible investment is constructed and tested on data relating to international differences in the diffusion of robot technology. The model provides a rigorous theoretical foundation for widely used empirical diffusion models. It predicts and the preliminary empirical estimates confirm that uncertainty, as measured by the volatility of several macroeconomic indicators, impacts significantly on the diffusion process. However, we find that volatility of several of our variables actually increases the adoption hazard.

**Key words**: Technological diffusion, uncertainty, risk, robots

**JEL Classification:**

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## 1. INTRODUCTION

Investment in general, and the adoption of new technology in particular, is a process inherently characterized by risk and uncertainty on both the cost and the demand side. At the same time, such investments would seem to be irreversible to at least the same extent as traditional investments. A new technology requires almost by definition additional investments in complementary human capital. Such investments are by their nature sunk and irreversible. The fact that the technology is new could mean that no, or only a limited, second hand market exists for such goods, increasing the degree of irreversibility further.

The investment literature, both theoretical and empirical, has made good use of the potential of models that make uncertainty and irreversibility the corner stones of analysis (for a recent example, see Caballero and Engel, 1999), although the empirical literature has placed little emphasis on analyzing the effects of uncertainty directly (but see Driver and Morton, 1991, Pindyck and Solimano, 1993, and Leahy and Whited, 1996). It is therefore somewhat surprising that the literature on the diffusion of technology has made little use of such models. The objective of this paper is to partly fill this gap by doing two things. First, by building a model of technology diffusion that is based on an optimizing firm (project holder) facing an irreversible investment choice in a world of uncertainty, and aggregating up to get an economy level expression for the diffusion of technology. We use a continuous time approach as that allows a relatively direct way of incorporating well-defined measures of uncertainty into the estimation equation. Second, by estimating the model using inter-country data on the diffusion of industrial robots, placing special emphasis on the effects of macro-level uncertainty on the adoption hazard. On the way, we provide a rigorous theoretical foundation for some widely used empirical models of technology diffusion, and show that these can be thought of as aggregate models of individual optimizing behavior, where an ad hoc structure has been placed on the adoption hazard. One would think that new technologies provide a good case for studying the effects of uncertainty, as the level of technological uncertainty is almost by definition greater than in investments in "old" technologies. As a consequence, any "environmental" uncertainty, such as that at the macro level, should have a greater impact as long as it is uncorrelated with the technological uncertainty of the new technology.

In the next section of this paper we develop a model of technology choice in a world of irreversibility and uncertainty. From that model we then construct an aggregate diffusion curve for an economy. In section 3 we discuss the nature of robot technology and the data on robot diffusion used to test the model. We demonstrate that investments in robots are more volatile than aggregate manufacturing investment. In section 4 we discuss econometric issues. In section 5 we present the results of the estimation and discuss their implications. We then use the estimated parameters in Section 6 to conduct policy experiments, in particular, to explore the effects of changing the volatility of the environment in which investment decisions are made. Section 7 contains the conclusions.

## 2. THE MODELING FRAMEWORK

We define a project (indexed by i) as an investment in a unit of robot technology.[1] At any time (indexed by t) in a country (indexed by j) we define $N_{jt}$ as the total number of

[1] This approach via projects can be contrasted with a more standard diffusion approach via firms. The latter approach however usually necessitates assumptions guaranteeing that intra firm diffusion is instantaneous.

projects that could be undertaken, or the total number of robots that could be used. We discuss $N_{jt}$ in more detail below. We assume that the returns to individual projects are independent of each other. We further define $M_{jt}$ as the number of robots installed, or the number of projects initiated at or before time t in country j. It is assumed that the adoption of a robot is an irreversible decision and robot technology has an infinite (physical) life.

**2.1 The adoption timing decision**

The model that we employ is adapted from a model by Dixit and Pindyck (1994, pp. 207 -211), first studied by McDonald and Siegel (1986). Defining $P_{jt}$ as the cost of a unit of robot technology in country j in time t, assumed the same for all projects i, and $R_{ijt}$ as the annual gross profit increase generated by project i in country j in time t, we assume that both $P_{jt}$ and $R_{ijt}$ are uncertain but exhibit geometric Brownian motion such that,

(1) $dR_{ijt}/R_{ijt} = \alpha_{Rij}dt + \sigma_{Rij}dz$

and that

(2) $dP_{jt}/P_{jt} = \alpha_{Pj}dt + \sigma_{Pj}dz$

where dz is the increment of a standard Wiener Process. Note that the $\alpha$ 's measure the expected rates of growth or drift of the variables over time while the $\sigma$ 's show the volatility or uncertainty attached to the variable. It is the impact of the $\sigma$ terms that in this paper measure the effects of uncertainty on the diffusion process.

For ease of exposition, we assume here that $P_{jt}$ and $R_{ijt}$ are independent covariates with zero covariance (but allow for nonzero covariance in the empirical model). We also

The former approach does not. As we do not actually have any firm level data no information is being lost by taking the project rather than the firm as the basic unit of analysis.

assume that $P_{jt}$ and $R_{ijt}$ are independent of the (existing) number of robots in use and actual dates of adoption. In terms of the diffusion literature this is the same as assuming that there are no stock and order effects in the diffusion process (see Karshenas and Stoneman, 1993). The resulting model thus falls within the class of probit or rank models of diffusion whereby different rates of adoption across countries will reflect the different characteristics of those countries, the characteristics being exogenous to the diffusion process.

Defining $r_{jt}$ as the riskless real interest rate in country j in time t, a project, which has not previously been undertaken, will be undertaken (started) in time t if and only if

(3) $R_{ijt}/P_{jt} \geq \rho_{ijt} \equiv \beta_{ij}(r_{jt} - \alpha_{Rij})/ (\beta_{ij} - 1)$

where $\rho_{ijt}$ is the threshold ratio of profit gains relative to the cost of acquisition above which project i will be undertaken in time t and below which it will not (this being allowed to be time dependent for generality), and $\beta_{ij}$ is the larger root of the quadratic equation

(4) $0.5.(\sigma_{Rij}^2 + \sigma_{Pj}^2).\ \beta_{ij}.(\beta_{ij} - 1) + (\alpha_{Rij} - \alpha_{Pj}).\beta_{ij} + (\alpha_{Pj} - r_{jt}) = 0$

enabling us to write (3) more generally as (5).

(5) $R_{ijt}/P_{jt} \geq \rho_{ijt} \equiv F(r_{jt}, \sigma_{Rij}^2, \sigma_{Pj}^2, \alpha_{Rij}, \alpha_{Pj})$

Following Dixit and Pindyck we assume that $r_{jt} - \alpha_{Rij} > 0$ and $r_{jt} - \alpha_{Pj} > 0$ which implies that $\beta_{ij} > 1$, and then using (3) and (4) we may deduce that $F_2 > 0$, $F_3 > 0$, $F_5 < 0$ but the signs of $F_1$ and $F_4$ are indeterminate. Thus increases in uncertainty ($\sigma_{Rij}^2, \sigma_{Pj}^2$) will lead to increases in the threshold value of $\rho_{ijt}$ and an increase in the drift rate of increase of robot prices will reduce the threshold, however the impact of an increase in the interest rate and the drift (rate of increase) of profit gains are indeterminate. Basically, although the direct impact of increases in the latter two parameters on ($r_{jt}$ - $\alpha_{Rij}$) is clear, their impact on $\beta_{ij}$ $\beta_{ij}$ – 1) is of the opposite sign. If there is no uncertainty so that $\sigma_{Rij} = \sigma_{Pj} = 0$ then (3) collapses to

(6) $R_{ijt}/P_{jt} \geq \rho_{ijt} = r_{jt} - \alpha_{Pj}$

which is the standard intertemporal arbitrage condition for adoption of a new technology in time t (see Ireland and Stoneman, 1986 ). In this case the impact of changes in $r_{jt}$ and $\alpha_{Rij}$ can be clearly signed as positive and zero respectively.

**2.2 The aggregate diffusion curve**

In this part we derive the aggregate diffusion curve, and relate it to the project level model of adoption presented above. This is undertaken at least partly with one eye upon the kind of inter-country data that is available to us.

*A. The generalized diffusion curve*

The data available to us upon the diffusion of robots indicates the number of robots owned in each country at each point of time. To generate a suitable variant of the modeling framework relevant for such data we define $h_{jt}$ as the probability that a project that has not been previously undertaken will be started in country j in time t. In the absence of any scrapping of the existing robot stock (a consequence of our assumption that R follows a geometric Brownian motion is that it is bounded below to be nonnegative and a robot will be operated forever),[2] one may then immediately write (7) as the expression for the increase in the stock of robots in country j in time t.

(7) $M_{jt} - M_{jt-1} = h_{jt}(N_{jt} - M_{jt-1})$

[2] One could allow for exit of robots by defining R=0 as an absorbing barrier.

Equation (7) is a logistic diffusion curve with the rate of diffusion given by the hazard rate, $h_{jt}$ and would be the same as the standard curve often used in diffusion analysis if $h_{jt}$ were a constant. A useful variant on (7) can be obtained using the approximation that $(x – y)/y \cong \log x – \log y$ which yields a Gompertz diffusion curve

(8) $\log M_{jt} – \log M_{jt-1} = h_{jt}\{\log N_{jt} – \log M_{jt-1}\}$.

Diffusion curves such as (7) and (8) are usually based upon information spreading or epidemic arguments (see Stoneman, 2001) but in this case that is not so. When they are so based the lagged stock usually appears on the on the right hand side as a proxy for current stock. In the current model the lagged stock appears in its own right.

One should note that in (7) and (8) $N_{jt}$ plays a somewhat different role than is often assumed in diffusion analysis. It is often assumed that as t tends to infinity the stock of new technology (in this case robots) tends to $N_{jt}$. Here however that is not necessarily so. Here, the diffusion process will continue only as long as $h_{jt}$ is positive and $h_{jt}$ may tend to zero well before $M_{jt} = N_{jt}$.

*B. Modeling the returns to adoption*

We do not have data upon the gross returns to robot adoption at either the project level, $R_{ijt}$, or macro level. To model $R_{ijt}$ we assume that

(9) $R_{ijt} = \exp(a_{ijt} + \Sigma_k b_k X_{kjt})$

The term $a_{ijt}$ reflects the heterogeneity of returns to different projects in country j, and we will be more precise about its nature below. It is reasonable to expect that different projects, even in a given country, will offer different returns. Determining factors, for example, might be the industry in which they are located and the demand conditions and factor prices in those industries. Alternatively it may be that projects are specific to firms and different firms face different returns to potential robot investment because of, for example, scale economies or different managerial efficiencies.

The term $\Sigma_k b_k X_{kjt}$ in (9) is a weighted sum of a number, k, of macroeconomic variables that are determinants of the returns to the adoption of robots. If the $X_{kjt}$ all follow an absolute, then $R_{ijt}$ follows a geometric Brownian motion so that (10) and (11) hold

(10) $\alpha_{Rij} = \Sigma_k b_k \alpha_{Xkj}$

(11) $\sigma^2_{Rij} = \Sigma_k b^2_k \sigma^2_{Xkj}$.

This approach ensures that $\rho_{ijt}$ is the same for all i for a given j and t and thus we may write, using (5), that

(12) $\rho_{ijt} = \rho_{jt} = F(r_{jt}, \Sigma_k b^2_k \sigma_{Xkj}{}^2, \sigma_{Pj}{}^2, \Sigma_k b_k \alpha_{Xkj}, \alpha_{Pj})$

where $F_2 > 0$ for all k.

In essence therefore (9) assumes that different projects in a given country yield different levels of gross returns from the use of the new technology (determined by macro economic factors and project specific effects) but the drift and volatility of the returns is the same for all projects in that country (but may differ across countries).

*C. Generating the hazard rate*

From (5), the condition for undertaking project i in time t may be written as

(13) $\ln R_{ijt} - \ln P_{jt} \geq \ln \rho_{jt}$

and after substitution from (10) and (11) this yields the adoption condition

(14) $a_{ij} + \Sigma_k b_k X_{kjt} - \ln P_{jt} - \ln \rho_{jt} \geq 0$

where $\rho_{jt}$ is given by (12). From the above it is clear that the way we model $a_{ij}$ will determine how $h_{jt}$, the hazard rate is to be specified.

Our model needs to be able – a priori – to explain within country heterogeneity in robot adoption. This naturally means that the returns to different projects within a country have to differ. One way of approaching this is to specify $a_{it}$ (we drop the country subscript j as superfluous for the moment) as:

(15) $a_{it} = \sqrt{1-d_1^2}h_i + d_1 e_{it}$.

In (15), $h_i$ is a project specific time-invariant (unobservable) term. We further assume that $h_i$ is distributed $N(0,1-d_1^2)$. The term $e_{it}$ is distributed $N(0,d_1^2)$ with $\text{cov}(e_{it},e_{i,t-1})=0$ and $\text{cov}(e_{it},h_i)=0$. Utilizing the distributional assumption of ε, the adoption probability in the first period for projects with the same project specific unobservable η can then be written as

(16) Prob(adopting in t=1|η=$\underline{\eta}$) =

$$\max\{0, \Phi\left[d_1^{-2}(\sqrt{1-d_1^2}\underline{h}_i - \ln r_1 + \sum_k b_k X_k - \ln P_1)\right]\}.$$

Equation (16) necessitates the assumption $d_1>0$. It is clear from (16) that the effects of the determinants of the adoption threshold on the adoption probability are opposite to their effects on the threshold. As our data shows that robot adoption is always strictly positive, we will make the simplifying assumption that the adoption probabilities are always strictly positive. Then, to get the population adoption probability, we need to integrate over η, yielding

(17) Prob(adopting in t=1)=

$$\int_{-\infty}^{\infty} \Phi\left[d_1^{-2}(\sqrt{1-d_1^2}\underline{h}_i - \ln r_1 + \sum_k b_k X_k - \ln P_1)\right] f(h_i) dh_i .$$

To derive the hazard rate of adoption for period t, first fix the value of the project specific unobservable to $\underline{\eta}$. Subtract all those projects that have already adopted. This yields the (discrete version of the) hazard rate of adoption conditional on the project specific unobservable as

(18) Prob(adoption in t|no adoption by end of period t-1, $\underline{\eta}$) $= \dfrac{\Phi_t(\underline{h}) - \Phi_{t-1}(\underline{h})}{1 - \Phi_{t-1}(\underline{h})}$ .

All the values of the cdf functions are now functions of $\underline{\eta}$. To get the population hazard, we again need to integrate over $\eta$. This yields

(19) Prob(adoption in t|no adoption by end of period t-1)

$$= \int_{-\infty}^{\infty} \frac{\Phi_t(h) - \Phi_{t-1}(h)}{1 - \Phi_{t-1}(h)} f(h) dh = h_{jt} \, .$$

Equation (19) provides the expression for the hazard rate in (8).

The formulation above has the attractive feature that it allows us to capture what most likely is an essential feature of the real world; not all projects that could technically utilise robots have equal expected revenues, and some differences could well be time-invariant.

As an example, it is well documented that adoption decisions depend positively on firm size (e.g. Rose and Joskow 1990, Karshenas and Stoneman, 1993). Consider that projects are distributed across firms in proportion to firm size, and that project returns increase with firm size and that firm size follows (approximately) a log-normal distribution in many countries. One could then interpret $h_i + e_{it}$ to measure the firm size realization of different projects and the above model would square nicely with the observed firm size – adoption correlation. As the model also has a time varying, zero auto-correlation error term, it also allows for the possibility that not all projects of the same size behave identically. In addition, it is possible that the smallest adopter is smaller than the largest non-adopter.

*D. Modeling the total number of projects*

What remains to fully specify the model is to consider how the total number of projects is to be determined. We have defined $N_{jt}$ as the number of projects where, technically, robots could be used, constituting thereby the total set of potential adoptions. $N_{jt}$ will be related to the nature of products produced in the economy and also the general type of production processes in place but has the important characteristic that it is independent of the costs or returns to the use of robot technology. It is worth repeating again, as stated above, that in this framework the diffusion process will continue only as long as $h_{jt}$ is positive and $h_{jt}$ may tend to zero well before $M_{jt} = N_{jt}$ thus it is not the case that as t tends to infinity the stock of new technology (robots) will necessarily (or be even expected to) tend to $N_{jt}$.

In Section 3 we discuss the nature of robot technology. It is clear that to some considerable extent robot technology is largely applicable in the manufacturing sector alone and thus a simple approach is to argue that the prime determinant of $N_{jt}$ is manufacturing output. In a first approach therefore it is assumed that $N_{jt}$ is related to manufacturing output $IND_{jt}$, in country j such that

(20) $$N_{jt} = IND_{jt}^{l}$$

## 3. ROBOT TECHNOLOGY AND DATA

### 3.1 Robot Technology

International statistics[3] on industrial robots are compiled by the UN and the International Federation of Robotics (IFR). These statistics cover 28 countries, 16 of which were included in our sample[4] although due to gaps in the data our panel is unbalanced, yielding a total of 161 observations. The sixteen countries are listed together with summary statistics in Table 1; the table also reports the observation period for each country. IFR has created an international standard (ISO TR 8373) that was used in compiling the statistics. Robots are customarily classified into standard and advanced robots and by the application area. However for the period 1981-1993 only aggregate data is available. It is estimated (the statistics are not water-tight) that there were some 610 000 robots in use worldwide at the end of 1993. The rate of growth of this stock has been fast, ranging from the 16-23% p.a. recorded at the turn of the decade to current levels of 6-8% p.a.. . The average yearly change in the robot stock varies between almost 30,000 in Japan to 41 in Norway.

As evidence that robot adoption is significant, but different from aggregate manufacturing investment, in 1993 robot investment amounted to 12% of total *machine tool* investments in the US, to 11% in both Germany and the UK and to 6% in France. Japan is by far the largest user of robots whether measured by absolute (some 60% of world stock) or relative numbers (in 1993 Japan had 264 advanced robots per 10 000 employees in manufacturing when the country with the second highest density (Singapore) had 61).

[3] Our discussion on robots and robot statistics relies heavily on **World Industrial Robots 1994**, Geneva, United Nations.

[4] 12 countries were excluded for a variety of reasons, for example, for Russia and Hungary there was no reliable data on macrovariables (and even the robot data is suspicious) and the Benelux countries (Netherlands, Belgium and Luxembourg) were summed together in the robot statistics.

Robots are used in several industries, and perform a variety of tasks. World-wide, the traditional "vehicle" for diffusion of robots has been the transport equipment industry (especially the motor vehicle industry), but lately e.g. in Japan, the electrical machinery industry has adopted more robots. The major application areas are welding, machining and assembly, with the leading application area varying over countries. Although it would certainly be beneficial to have more detailed country level data on the composition of the robot stock, and its use, such country-level idiosyncrasies are to a great extent constant over time, and can be captured by country-level controls in the econometrics model.

Intuition suggests that investments into a new technology such as robots may be more volatile than aggregate manufacturing investment. The reason is that as the degree of technological uncertainty is greater (leading to a greater variance of future revenue streams), such investments are more sensitive to changes in other variables (such as prices, and interest rates) that affect investment decisions. To check whether this is the case, we compared manufacturing investment volatility to that of robot diffusion volatility in the OECD countries of our sample (thereby excluding Singapore, Switzerland and Taiwan, for which it proved difficult to obtain a comparable investment series at this point). To be able to compare two different forms of investment that are measured differently (manufacturing investment in monetary terms, robots in units), we employed the coefficient of variation. Comparing for each of the 13 countries the two series over the robot observation period (see Table 1) we found that for all countries, the coefficient of variation of robot diffusion was larger than that of aggregate manufacturing investment (which includes robots, thereby biasing these figures upwards). The mean ratio of robot coefficient of variation to that of manufacturing investment was 3.60, with a minimum of 1.26 (Sweden) and a maximum of

5.74 (France). We read this as evidence that robot diffusion indeed is more volatile than aggregate manufacturing investment.

TABLE 1 SOMEWHERE HERE

Robot price data were not available on an individual country basis, but we located such data for Germany (and Italy). The results that we present are based on the German data. The prices were converted into real U.S. dollars using the respective consumer price index and the yearly (average) exchange rates as reported in IMF's International Financial Statistics Yearbook.

**3.2 Macro data**

The data on macrovariables comes mainly (but not solely, see the Data Appendix) from Penn World Tables Mark 6 (Summers and Heston, 1991). The relevant variables (see Section 4 below) are GDP, the investment share of GDP, the real interest rate (taken from IFS statistics) and the rate of inflation measured using the Penn World Tables' index on consumer prices.

TABLE 2 SOMEWHERE HERE

Table 2 reveals that there is considerable variation in the macrovariables over countries. The mean of GDP growth varies between 11.72% (Taiwan) and 4.4% (Norway). The mean of the real interest rate varies between 0.69% (Switzerland) and 7.45% (Taiwan) whereas the lowest mean inflation rate is found in USA (1.3%) and the highest in Spain (11.1%). There are also considerable inter-country differences in the volatility measures, but the different measures do not necessarily move in parallel.

For the drift and volatility of these variables, we use the ML estimates of average annual growth and its standard deviation, calculated over the period 1975-1992. In the appendix we report Dickey-Fuller unit root tests employing all the data available in the Penn world tables (usually but not uniformly from 1940 to 1991); for none of the series can we reject the Null of a random walk. As noted e.g. by Dixit and Pindyck, (1994), it is very much possible that these results would change had we more data available. As this is not the case, we proceed on the assumption that the macro level time series are well approximated by random walks with drift.

## 4. ECONOMETRIC ISSUES

There are several econometric modeling issues that need to be tackled:

**Specification of the model**. We proceed by assuming that the potential profit gain from installing robots is driven by three main macroeconomic indicators, viz. real gross domestic product GDP, the share of investment in GDP, I/GDP, and the general price level, PI. *In other words, these three variables constitute the vector* $X_{jt}$. The logic for the variables included is that demand conditions as measured by GDP and the general price level will be a main determinant of profit gains from adoption, whereas I/GDP will reflect the general investment climate and thus also the profitability of robot adoption. One may note that no cost indicators e.g. factor prices appear in this formulation. Although such cost indicators will affect the profitability of adoption, the I/GDP variable is a reduced form variable that will pick up such influences (as well as many others e.g. the buoyancy of expectations). One might argue that I/GDP could also be said to pick up the influence of the general price level. We have however included this separately because so much of the literature on investment and uncertainty stresses the potential impact of the drift and volatility of the price level (inflation and changes therein). It is important to note that strictly speaking, inflation is a drift variable, not a volatility variable. Although the popular view is that inflation impedes investment, one can build an argument for exactly the opposite by noting that the level of consumer prices could measure the price of outputs of robot adopters, rather than the cost of inputs. In that case increases in the drift of the consumer prices would mean higher expected prices in the future, thereby increasing discounted profits, and lowering the adoption threshold. We find (empirically) that GDP, I/GDP and the price level each follow an absolute Brownian motion and thus their weighed sum will also do so.

Given our limited sample size, we have mainly chosen to parameterize the model to gain efficiency. We therefore maintain the assumption that both unobservables in R are normally distributed. Our specific theoretical model does yield an explicit (but complicated) expression for ρ. Instead of using that, we approximate lnρ with a low order polynomial, restricting some cross terms to have zero coefficients (to reduce the number of parameters to be estimated), thereby estimating it semi-parametrically.

We employ the Gompertz specification of the aggregate diffusion curve (equation (8)) as previous work with the same data suggests that this fits the data considerably better than the logistic (equation (7)).

**Error structure**. An important issue relating to the error structure rises from the cross-country nature of our data. It is very likely that e.g. the potential number of robots varies over countries in a manner that is country specific, time-invariant, and unobservable to us. This suggests the use of a random effects specification. We could write

(20') $$N_{jt} = IND_{jt}^{q} e^{c t_j}$$

where $\tau$ is distributed $N(0,\chi^2)$, and the country specific time-invariant error term is (after taking logs; see equation (14)) multiplied by $h_{jt}$. This creates a random coefficients – type (equi-correlated) model that cannot be estimated with standard methods.

**Initial conditions**. It is well known that initial conditions (we do not observe robot diffusion from T=0) may be correlated with time-invariant unobservables (Heckman, 1981). Note however that we do observe country-wise robot stocks "almost" from the beginning (essentially apart from France): this is likely to reduce the problem considerably. As can be seen from Table 3, for twelve out of sixteen countries, the first observed stock accounts for less than 13% of final observed stock and for some, substantially less. For four countries, the first observed stock is over 20% of the final observed stock. These countries are Australia (29,97%, 1st observation year 1984), France (40.44%, 1987), Norway (26.04%, 1982), and Sweden 24.73%, 1982). Together, these countries account for 4% of sample robot stock at the end of 1992. It would therefore seem that initial conditions do not pose a serious problem in our data.

TABLE 3 SOMEWHERE HERE

**Endogeneity of price terms**. Although it may be plausible to think that individual firms take prices as given when contemplating the adoption of robots, it is less plausible to assume that the price of robots is exogenous at the country level. This would seem to be the case at least for the countries with higher adoption rates (Japan being the prime example). We therefore test for the exogeneity of robot prices in the future.

**Aggregation**. Our current framework assumes that there is no connection between the unobservables in $R_{jt}$, and the number of potential robots, $N_{jt}$. In future work we plan to exploit the knowledge that i) large firms usually adopt earlier (e.g. Rose and Joskow, 1990, Karshenas and Stoneman, 1993) and ii) the firm size distribution is (close to) log-normal. By assuming that industrial output is the sum of $h_i + e_{it}$ over all firms in country j, we can connect the hazard rate to $N_{jt}$.

**Estimation methods**. We use a generalized method of moments estimator (GMM) and a method of simulated moments estimator (MSM) respectively, for models with and without a time-invariant error term. Both estimators minimize the difference between the first moments of the data and the model. Currently we use S=40, where S is the number of simulations, for the MSM estimator. We use simulation to estimate the hazard rate, and the country specific unobservable τ. We simulate them by drawing pseudo random numbers from a standard normal with zero mean and unit variance. As the variance of η is $1-d_1^2$, and the coefficient $\sqrt{1-d_1^2}$, we utilize the fact that for $f(\hat{h}) = f(\frac{h}{\sqrt{1-d_1^2}})$ to hold (where $\hat{h}$ is the draw from the standard normal), $h = \hat{h}\sqrt{1-d_1^2}$. That is, to transform the distribution from a standard normal to N(0, $1-d_1^2$), we insert the $\hat{h}$'s into the objective function and impose a unit coefficient onto them.

**Instruments**. Both estimators require instruments. Berndt et al. (1974) show that optimal instruments are of the form

(21) $A^*(x_{jt}) = G \circ D(x_{jt})'\Omega^{-1}$

where γ is a vector of parameters, $x_{jt}$ is a data vector,

(22) $D(x_{jt}) = E\lfloor \partial j_{jt} / \partial g | x_{jt} \rfloor$

where $j_{ijt}$ is the distance between data and model moments, and

(23) $\Omega = E\lfloor j_{jt} j'_{jt} | x_{jt} \rfloor$.

These, however, suffer from reliance on functional form assumptions: if there is functional form misspecification, the resulting estimator is consistent but inefficient (Newey, 1990). Newey (1990) has proposed instruments that are asymptotically optimal even under functional form misspecification. Currently we use (untransformed) explanatory variables as instruments.

**Generated regressors**. Our drift and volatility variables are generated, leading to biased standard errors. The problem is exacerbated in our model as the generated regressors appear in a (highly) nonlinear context. Currently, we are not making this correction.

## 5. RESULTS (VERY PRELIMINARY)

The estimation results are presented in Table 4. Looking first at the levels variables, we find that I/GDP and (log of) robot prices affect the hazard rate negatively, GDP and the real interest rate positively. Of these, the I/GDP sign is contrary to expectations, the others either as expected, or (in the case of the real interest rate) theoretically undetermined. Our estimates suggest that the (log of the) number of potential adopters is 0.02 times that industrial output. We inserted a full vector of time dummies into the hazard rate specification to control for period specific unobservables such as changes in the quality of robots (normalizing the coefficient of year 1981 to zero). We find that all time dummies' coefficients up to and including 1987 are positive and significant, those for later years negative and significant.

TABLE 4 SOMEWHERE HERE

Turning then to the drift variables, we find that the drift of I/GDP has a positive impact, and its square a negative one. Within sample values the effect is negative and in line with the negative coefficient on the levels term. For robot prices, the signs are reversed, but again within sample values the effect is negative and this time contrary to expectation. For GDP, the combined effect is positive as predicted, even though the second order term carries a negative coefficient. Finally, we find that the drift of the price level, i.e., inflation, obtains negative coefficients for both the linear and the second order terms. This is in line with the popular view that inflation has a negative impact on investment.

Theory predicts that volatility increases the adoption threshold. In our semi-parametric specification of the investment threshold, we allowed for interaction terms between the different volatility variables and have therefore calculated the marginal effects of volatility on the adoption threshold by its source, holding other types of volatility at their sample means. These calculations reveal that if one ignores the interaction terms, the "direct" effect of all types of volatility, but that of the volatility of I/GDP, are negative. Taking the highly significant interaction terms into account changes the picture in that now only the volatility of the price level has a positive effect on the adoption threshold. In other words, the interaction terms change the signs of the partial derivatives of the (log of) the adoption threshold with respect to the volatility of I/GDP and price level.

Finally, our set up allows potentially for the estimation of the variance shares of the time-invariant and time varying components of the unobservable in R. However, the estimated values rarely diverge from their starting values by much. We have therefore done limited robustness experiments and found that the results presented are remarkably robust to large changes in the (starting) value of this parameter.

## 6. POLICY EXPERIMENTS

TO BE WRITTEN

## 7. CONCLUSIONS

In this paper, we have built an economy level model of technology diffusion that is based on micro-level optimizing behavior. We show that the traditionally used empirical models can be cast in this framework, the difference being that the parameter, which has been called “the adjustment speed” previously, is actually the adoption hazard.

Our model allows for project specific permanent unobservables, as well as time-varying unobservable differences in project returns. The project level model also shows how to incorporate measures of uncertainty into the diffusion model, and what measures of uncertainty to use. We estimate the model using a data set on the international diffusion of industrial robots.

Our current estimates suggest that uncertainty plays an important role in determining the adoption speed of industrial robots, but in a way that is to a large extent incompatible with theory. Of our five identified sources of volatility, namely the volatility of I/GDP, GDP, robot prices, inflation (drift of the price level), and the volatility of the price level, only the last two have the predicted negative impact on the speed of adoption. The other three sources of volatility increase adoption hazard.

## REFERENCES


Berndt, E. R., B. H. Hall, R. E. Hall, and J. A. Hausman, (1974), "Estimation and Inference in Nonlinear Structural Models", *Analysis of Economic and Social Measurement*, 3, 653-666.

Caballero R- J. and Engel E. M. R. A., (1999), "Explaining investment dynamics in US manufacturing: A generalized (S,s) approach", *Econometrica,*

Dixit A., and R. Pindyck (1994), *Investment Under Uncertainty*, Princeton, Princeton University Press.

Driver C., and D. Moreton (1991), "The Influence of Uncertainty on UK Manufacturing Investment", *Economic Jo*urnal, 101, 1452 - 59

Heckman J., (1981), "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process", in Manski and McFadden (eds.) Structural Analysis of Discrete Data with Econometric Applications, MIT Press

Karshenas K., and P. Stoneman (1993), "Rank, Stock, Order and Epidemic Effects in the Diffusion of New Process Technology", *Rand Journal of Economics*, 24, 4, 503-528, Winter 1993.

Leahy, J., and Whited. T., (1996), "The Effect of Uncertainty on Investment: Some Stylized Facts", *Journal of Money, Credit and Banking*, 28, 64-83.

Mansfield E., (1968), *Industrial Research and Technological Innovation*, New York, Norton.

McDonald, R., and Siegel, D., (1986), "The value of waiting to invest", *Quarterly Journal of Economics*, 101, 707-727.

Newey, W. K., (1990), "Efficient Instrumental Variables Estimation of Nonlinear Models", *Econometrica*, 58, 4, 809-837.

Pagan A. R., (1984). "Econometric Issues in the Analysis of Regressions with Generated Regressors", *International Economic-Review*; 25(1), 221-47.

Pindyck R. S , and A. Solimano (1993), "Economic Instability and Aggregate Investment", *NBER Macroeconomics Annual*, 259 – 303.

Rose, N. and P. Joskow (1990), "The Diffusion of New Technologies: Evidence from the Electricity Utility Industry", *Rand Journal of Economics*, 21, 354 – 373.

Stoneman, P. (1983), *The Economic Analysis of Technological Change*, London, Oxford University Press

Stoneman, P., (2001), *The Economic Analysis of Technological Diffusion*, Blackwell. Oxford, forthcoming.

Summers, R. and Heston, A., (1991), "The Penn World Table (Mark 5): An Expanded Set of International Comparisons, 1950-1988", *Quarterly-Journal-of-Economics*; 106(2), 327-68.

Toivanen, O., P. Stoneman and P. Diederen (1999),"Uncertainty, Macroeconomic Volatility and Investment in New Technology", in C Driver (ed.), *Investment, Growth and Employment: Perspectives for Policy*, 136 – 160, 1999, London, Routledge

## DATA APPENDIX

1. Data sources and variable definitions

- robot and robot price data: World industrial robots 1994, United Nations. For robot prices, we use the German prices on the unit value of robot production. Prices for 1979 and 1978 were calculated using the results of a regression of prices on a constant, years and squared years. The price series was deflated using the consumer price index reported in the IFS statistics (the only price series available for all countries). We use prices in constant 1985 US dollars for all countries in the regressions. To calculate drift and volatility for robot prices we use the whole series.
- GDP, from Penn World Tables Mark 5.6. Defined as GDP = real GDP per capita (series name CGDP) times population in 000's (POP)/1000 000. To calculate drift and volatility for GDP, we use 1960-1992 data, as this was the longest series available to all countries.
- Manufacturing output. Manufacturing in 1986 defined as Man. = index of manufacturing times GDP (defined as above) times the manufacturing share of GDP. For other years, the level of manufacturing is calculated from the 1986 (1992 for Taiwan, see below) figure using the index of manufacturing. The index is from International Financial Statistics (for Taiwan from Financial Statistics, Taiwan District Republic of China: these are designed to conform to the IFS statistics) and GDP is derived from Penn World Tables as described above. The share of manufacturing as a per cent of GDP in1986 is from the UN Statistical Yearbook 1995 for all other countries but Italy and Taiwan (not available for these two). For Italy, the manufacturing share of GDP was calculated as the ratio between figures "industria in

senso stretto" (total industry output) and "totale" in Table "Tavola 10 – Produzione al costo dei fattori – Valori a prezzi 1995" (Table 10 – Production at factor cost – 1995 values"). The table can be found on the web page of the National Institute of Statistics of Italy (http://www.istat.it/) as file TAVOLE-PRODUZIONE.XLS. The manufacturing share of GDP was calculated for 1986. For Taiwan, the source is the file VIGNOF4D.XLS to be found on the web page of the Directorate General of Budget, Accounting and Statistics of Taiwan (http://www.dgbasey.gov.tw/). The file contains Table H-2 Structure of Domestic Production, in which the manufacturing share of GDP is reported for 1992-1995. We used the 1992 figure.

- Investment share of GDP: Penn world tables (CI). Drift and volatility calculations as with GDP.
- Consumer price level, Penn World Tables (PI). Inflation in country i in year t defined as $infl_{it} = \ln(PI_{it}) - \ln(PI_{it-1})$.
- real interest rate. Defined as the difference between the nominal interest rate and inflation, both calculated from indexes from the IFS. Inflation is calculated from the consumer price index as reported in IFS (it is the only price index available for all sample countries in IFS). We use the money market rate from IFS statistics as the nominal interest rate.

2. Testing the assumption of a random walk

(PRELIMINARY: MORE TESTING TO BE DONE)

Our theoretical model assumes that the relevant (country-level) time-series are random walks (with drift). In the estimations, we use as explanatory variables ML estimates of the drift (growth rate) and standard error of GDP, investment share of GDP, and of robot prices. To test that our time-series are random walks, we regressed the difference in the series on a constant, time trend, and lagged level using data from the period 1960-1992 (we also estimated the model with out the time trend, with similar results). We then calculated a Dickey-Fuller test. Table A.1 below summarises our findings, presenting the D-F test value (p-value) of the GDP and I/GDP estimations for each country separately (32 degrees of freedom), and finally the robot price tests.

TABLE A.1
DICKEY FULLER TESTS

| Country | GDP | I/GDP |
|---|---|---|
| Australia | 1.3640 | 4.4769 |
| | (1.0000) | (1.0000) |
| Austria | 0.0234 | 2.3260 |
| | (1.0000) | (1.0000) |
| Denmark | 1.1187 | 2.5019 |
| | (1.0000) | (1.0000) |
| Finland | 2.0427 | 2.8554 |
| | (1.0000) | (1.0000) |
| France | 1.0780 | 2.2507 |
| | (1.0000) | (1.0000) |
| Germany | 1.5006 | 2.9139 |
| | (1.0000) | (1.0000) |
| Italy | 0.9978 | 3.0360 |
| | (1.0000) | (1.0000) |
| Japan | 1.1567 | 2.0718 |
| | (1.0000) | (1.0000) |
| Norway | 1.9845 | 1.9929 |
| | (1.0000) | (1.0000) |
| Singapore | 2.8244 | 1.6285 |
| | (1.0000) | (1.0000) |
| Spain | 0.8829 | 1.8924 |
| | (1.0000) | (1.0000) |
| Sweden | 2.0859 | 2.9694 |
| | (1.0000) | (1.0000) |
| Switzerland | 0.5560 | 2.2222 |
| | (1.0000) | (1.0000) |
| Taiwan | 4.6409 | 1.3666 |
| | (1.0000) | (1.0000) |
| UK | 1.8332 | 2.5871 |
| | (1.0000) | (1.0000) |
| USA | 1.3868 | 4.3405 |
| | (1.0000) | (1.0000) |

TABLE 1
VOLATILITY OF ROBOT ADOPTION IN COMPARISON TO MANUFACTURING INVESTMENT

| Country | Ratio of robot diffusion coefficient of variation to manufacturing investment coefficient of variation |
|---|---|
| Australia | 4.15677 |
| Austria | 5.43715 |
| Denmark | 3.340727 |
| Finland | 1.91579 |
| France | 5.724699 |
| Germany | 2.729275 |
| Italy | 4.548866 |
| Japan | 1.73117 |
| Norway | 2.944321 |
| Spain | 2.780212 |
| Sweden | 1.256557 |
| UK | 1.422169 |
| USA | 5.592314 |

TABLE 2
COUNTRY-LEVEL DESCRIPTIVE STATISTICS

| COUNTRY | GDP Millions of 1985 US dollars | GDP growth % | GDP growth | GDPgrowth s.d. | Investment share of GDP (I/GDP) per cent | %-change in I/GDP | I/GDP growth | I/GDP growth s.d. | Inflation |
|---|---|---|---|---|---|---|---|---|---|
| Australia | 271.7382 | 0.0594 | 0.0812 | 0.0347 | 25.6375 | -0.0183 | -0.0064 | 0.0802 | -0.0008 |
| 1985-1991 | 41.1980 | 0.0310 | | | 2.2772 | 0.0757 | | | 0.09607 |
| Austria | 98.6655 | 0.0644 | 0.0822 | 0.0279 | 24.7909 | 0.0035 | 0.0073 | 0.0641 | 0.0300 |
| 1982-1992 | 21.5569 | 0.0163 | | | 1.7335 | 0.0540 | | | 0.1273 |
| Denmark | 74.6674 | 0.0633 | 0.0749 | 0.0242 | 21.2909 | -0.0015 | -0.0096 | 0.0914 | 0.0217 |
| 1982-1992 | 14.6161 | 0.0191 | | | 2.0364 | 0.0843 | | | 0.1299 |
| Finland | 67.5622 | 0.0535 | 0.0785 | 0.0467 | 30.5182 | -0.0315 | -0.0127 | 0.0976 | 0.0050 |
| 1982-1992 | 13.2520 | 0.0506 | | | 3.4713 | 0.0959 | | | 0.1073 |
| France | 948.4007 | 0.0622 | 0.0821 | 0.0226 | 26.8200 | 0.0040 | 0.0021 | 0.0549 | 0.0213 |
| 1988-1992 | 86.0395 | 0.0191 | | | 1.0208 | 0.0512 | | | 0.0920 |
| Germany | 933.3297 | 0.0685 | 0.0801 | 0.0258 | 23.9727 | -0.0011 | -0.0077 | 0.0522 | 0.0221 |
| 1982-1992 | 228.9880 | 0.0196 | | | 0.8855 | 0.0332 | | | 0.1256 |
| Italy | 729.1065 | 0.0629 | 0.0843 | 0.0291 | 24.1364 | -0.0029 | -0.0083 | 0.0655 | 0.0401 |
| 1982-1992 | 158.3957 | 0.0141 | | | 0.6772 | 0.0341 | | | 0.1144 |
| Japan | 1739.0154 | 0.0787 | 0.1080 | 0.0319 | 34.4273 | 0.0094 | 0.0155 | 0.0591 | 0.0309 |
| 1982-1992 | 468.7260 | 0.0166 | | | 3.3142 | 0.0443 | | | 0.1297 |
| Norway | 61.6330 | 0.0461 | 0.0802 | 0.0457 | 27.7000 | -0.0247 | -0.0114 | 0.0965 | 0.0321 |
| 1983-1992 | 7.7665 | 0.0391 | | | 3.7205 | 0.1011 | | | 0.1014 |
| Singapore | 28.9984 | 0.1064 | 0.1284 | 0.0595 | 35.8000 | -0.0049 | 0.0121 | 0.0811 | 0.0042 |
| 1982-1992 | 10.4600 | 0.0460 | | | 3.6927 | 0.0808 | | | 0.0489 |
| Spain | 387.2430 | 0.0737 | 0.0922 | 0.0262 | 25.3778 | 0.0240 | 0.0117 | 0.0546 | 0.0747 |
| 1984-1992 | 87.2258 | 0.0242 | | | 3.5643 | 0.0607 | | | 0.1023 |
| Sweden | 128.5969 | 0.0545 | 0.0705 | 0.0273 | 21.4909 | 0.0045 | -0.0036 | 0.0833 | 0.0224 |
| 1982-1992 | 24.3775 | 0.0210 | | | 2.1741 | 0.0771 | | | 0.1184 |
| Switzerland | 117.1019 | 0.0606 | 0.0750 | 0.0242 | 30.9800 | 0.0064 | 0.0035 | 0.0800 | 0.0363 |
| 1983-1992 | 23.1568 | 0.0190 | | | 2.6599 | 0.0542 | | | 0.1372 |
| Taiwan | 130.6258 | 0.1172 | 0.1306 | 0.0349 | 22.5667 | -0.0205 | 0.0214 | 0.0955 | 0.0264 |
| 1982-1990 | 44.1117 | 0.0302 | | | 2.1575 | 0.0947 | | | 0.0814 |
| UK | 742.3100 | 0.0605 | 0.0699 | 0.0252 | 17.8727 | 0.0189 | 0.0027 | 0.0771 | 0.0048 |
| 1982-1992 | 153.1283 | 0.0227 | | | 1.6298 | 0.0642 | | | 0.1041 |
| USA | 4250.0572 | 0.0577 | 0.0749 | 0.0251 | 22.0833 | -0.0038 | -0.0023 | 0.0638 | 0.0058 |
| 1982-1992 | 1370.0140 | 0.0224 | 0.0016 | | 1.8004 | 0.0706 | 0.0016 | 0.0042 | 0.0062 |

NOTES: First column gives the country name and period used in estimation (which is due to differencing one year less than the observation period). In most cases, robot data limits the observation period. Each column gives the country level mean and s.d. of the respective variable. Note that e.g. the GDP growth % and GDP growth differ because the former is calculated over the robot stock observation period only, the latter over a longer period (defined in the data appendix ). For the drift (growth) and volatility variables, no s.d.'s are reported as they are by definition zero.

TABLE 2
COUNTRY-LEVEL DESCRIPTIVE STATISTICS

| COUNTRY | Robot stock # robots | Change in robot stock | %-change | Robot price RP 1985 US dollars | RP drift | RP s.d. | Real interest rate Percentage points | Industrial production Millions of 1985 US dollars |
|---|---|---|---|---|---|---|---|---|
| Australia | 1229.3750 | 154.2500 | 0.1506 | 98.9510 | 0.0832 | 0.2139 | 6.3238 | 59.6261 |
| 1985-1991 | 402.7757 | 50.1960 | 0.0683 | 31.0942 | | | 1.3662 | 2.1126 |
| Austria | 667.6364 | 150.0909 | 0.3091 | 90.4676 | 0.0497 | 0.2007 | 4.6629 | 13.9798 |
| 1982-1992 | 566.1875 | 101.2496 | 0.0808 | 29.8562 | | | 0.9528 | 4.4845 |
| Denmark | 301.4545 | 48.4545 | 0.2216 | 90.4676 | 0.0760 | 0.2102 | 7.0989 | 11.4156 |
| 1982-1992 | 193.6958 | 29.7098 | 0.1095 | 29.8562 | | | 1.4206 | 1.0931 |
| Finland | 494.2727 | 92.3636 | 0.3093 | 90.4676 | 0.0756 | 0.2182 | 6.1285 | 13.8356 |
| 1982-1992 | 342.9624 | 37.4039 | 0.1797 | 29.8562 | | | 3.0889 | 1.1285 |
| France | 8380.2000 | 1289.0000 | 0.1811 | 114.1126 | 0.0810 | 0.2144 | 6.0377 | 176.1589 |
| 1988-1992 | 2071.8759 | 180.4896 | 0.0638 | 29.4699 | | | 0.4904 | 3.8855 |
| Germany | 17533.1818 | 3371.8182 | 0.2582 | 90.4676 | 0.0516 | 0.2016 | 3.8156 | 282.7428 |
| 1982-1992 | 12165.3533 | 1782.6613 | 0.0856 | 29.8562 | | | 1.1037 | 30.7243 |
| Italy | 7573.3636 | 1513.3636 | 0.3307 | 90.4676 | 0.0962 | 0.2194 | 4.6662 | 2.5276 |
| 1982-1992 | 5451.8190 | 685.0799 | 0.1996 | 29.8562 | | | 1.8523 | 0.2000 |
| Japan | 167296.6364 | 29859.8182 | 0.2556 | 90.4676 | 0.0333 | 0.2238 | 3.7269 | 472.7758 |
| 1982-1992 | 111333.3099 | 14306.0971 | 0.1040 | 29.8562 | | | 0.7464 | 65.7128 |
| Norway | 422.4000 | 42.6000 | 0.1345 | 93.0191 | 0.0817 | 0.2150 | 5.5871 | 9.1056 |
| 1983-1992 | 128.8825 | 19.0916 | 0.0970 | 30.1806 | | | 1.4845 | 1.2137 |
| Singapore | 807.4545 | 189.5455 | 0.5487 | 90.4676 | 0.0457 | 0.3636 | 5.7492 | 7.0426 |
| 1982-1992 | 798.0270 | 238.4023 | 0.4845 | 29.8562 | | | 5.6178 | 2.9696 |
| Spain | 1642.1111 | 342.2222 | 0.2326 | 96.0272 | 0.0902 | 0.2308 | 6.4693 | 85.6590 |
| 1984-1992 | 1006.8790 | 217.3671 | 0.0287 | 30.3798 | | | 2.7346 | 5.5779 |
| Sweden | 2781.2727 | 311.3636 | 0.1270 | 90.4676 | 0.0877 | 0.2199 | 5.8330 | 26.0212 |
| 1982-1992 | 1106.0298 | 89.7700 | 0.0318 | 29.8562 | | | 3.9539 | 1.6903 |
| Switzerland | 868.5000 | 197.7000 | 0.3335 | 93.0191 | 0.0524 | 0.1924 | 0.6964 | 28.3199 |
| 1983-1992 | 695.1109 | 132.3976 | 0.1330 | 30.1806 | | | 1.0631 | 2.8359 |
| Taiwan | 462.4444 | 143.5556 | 0.7961 | 88.0445 | 0.0422 | 0.2668 | 7.4458 | 53.4771 |
| 1982-1990 | 435.5362 | 111.3217 | 0.8907 | 32.7886 | | | 1.8341 | 10.2842 |
| UK | 4301.5455 | 625.9091 | 0.2151 | 90.4676 | 0.0576 | 0.2045 | 4.6691 | 146.1418 |
| 1982-1992 | 2150.9057 | 127.8870 | 0.1345 | 29.8562 | | | 1.4663 | 9.3619 |
| USA | 25849.8333 | 3468.6667 | 0.1787 | 91.6561 | 0.0686 | 0.2447 | 4.8861 | 800.3874 |
| 1982-1992 | 14659.5393 | 1890.8775 | 0.1376 | 28.7630 | 0.0035 | 0.0127 | 1.6758 | 221.5590 |

NOTES: First column gives the country name and period used in estimation (which is due to differencing one year less than the observation period). In most cases, robot data limits the observation period. Each column gives the country level mean and s.d. of the respective variable. Note that e.g. the GDP growth % and GDP growth differ because the former is calculated over the robot stock observation period only, the latter over a longer period (defined in the data appendix ). For the drift (growth) and volatility variables, no s.d.'s are reported as they are by definition zero.

TABLE 3
COUNTRY LEVEL INITIAL STOCKS AND FINAL STOCKS OF ROBOTS

| Country | Initial stock of robots | Final stock of robots | Ratio of initial to final stock of robots | 1st year of observation/ # obs. |
|---|---|---|---|---|
| Australia | 528 | 1762 | 0.2997 | 1984/7 |
| Austria | 57 | 1708 | 0.0334 | 1981/11 |
| Denmark | 51 | 584 | 0.0873 | 1981/11 |
| Finland | 35 | 1051 | 0.0333 | 1981/11 |
| France | 4376 | 10821 | 0.4044 | 1987/5 |
| Germany | 2300 | 39390 | 0.0584 | 1981/11 |
| Italy | 450 | 17097 | 0.0263 | 1981/11 |
| Japan | 21000 | 349458 | 0.0601 | 1981/11 |
| Norway | 150 | 576 | 0.2604 | 1982/10 |
| Singapore | 5 | 2090 | 0.0024 | 1981/11 |
| Spain | 433 | 3513 | 0.1233 | 1983/9 |
| Sweden | 1125 | 4550 | 0.2473 | 1981/11 |
| Switzerland | 73 | 2050 | 0.0356 | 1982/10 |
| Taiwan | 1 | 2217 | 0.0005 | 1981/9 |
| UK | 713 | 7598 | 0.0938 | 1981/11 |
| USA | 6000 | 47000 | 0.1277 | 1981/11 |

TABLE 4
ESTIMATION RESULTS

| Variable/parameter | (1) GMM |
|---|---|
| Baseline hazard | |
| Constant/$\beta_0$ | - |
| GDP/$\beta_1$ | 0.000206 |
| | 0.000000 |
| $\alpha_{GDP}/\beta_{11}$ | 4.968712 |
| | 0.00869 |
| $\alpha^2_{GDP}/\beta_{12}$ | -3.451337 |
| | 0.025332 |
| $\sigma_{GDP}/\beta_{13}$ | -0.397163 |
| | 0.008947 |
| $\sigma^2_{GDP}/\beta_{14}$ | -3.121666 |
| | 0.117557 |
| I/GDP/$\beta_2$ | -0.0012 |
| | 0.0001 |
| $\alpha_{IGDP}/\beta_{21}$ | 0.061762 |
| | 0.025885 |
| $\alpha^2_{IGDP}/\beta_{22}$ | -1.049791 |
| | 0.608599 |
| $\sigma_{IGDP}/\beta_{23}$ | 3.976006 |
| | 0.010012 |
| $\sigma^2_{IGDP}/\beta_{24}$ | 0.078959 |
| | 0.006117 |
| lnP/$\beta_3$ | -0.024560 |
| | 0.000086 |
| $\alpha_P/\beta_{31}$ | -5.236258 |
| | 0.009672 |
| $\alpha^2_P/\beta_{32}$ | 0.651282 |
| | 0.034230 |
| $\sigma_P/\beta_{33}$ | 3.513657 |
| | 0.000600 |
| $\sigma^2_P/\beta_{34}$ | 12.192355 |
| | 0.007358 |
| r/$\beta_4$ | 0.021415 |
| | 0.000064 |
| i/$\beta_{51}$ | -14.852534 |
| | 0.035978 |
| $i^2/\beta_{52}$ | -1.948580 |
| | 0.469109 |
| $\sigma_i/\beta_{53}$ | 0.033383 |
| | 0.006828 |
| $\sigma^2_i/\beta_{53}$ | 0.198876 |
| | 0.073622 |
| $\sigma_{I/GDP}\sigma_P$ /$\beta_{53}$ | 4.557470 |
| | 0.022868 |
| $\sigma_{I/GDP}\sigma_i/\beta_{53}$ | -0.952449 |
| | 0.078442 |
| $\sigma_{I/GDP}\sigma_{GDP}/\beta_{53}$ | 1.271087 |
| | 0.139501 |
| $\sigma_P\sigma_i/\beta_{53}$ | -0.027212 |
| | 0.039015 |
| $\sigma_P\sigma_{GDP}/\beta_{53}$ | 4.848620 |
| | 0.055216 |
| $\sigma_i\sigma_{GDP}/\beta_{53}$ | 0.387525 |
| | 0.138850 |
| $d_1$ | 0.500000 |
| | 0.000001 |
| Frictionless robot stock | |
| lnIND/$\lambda$ | 0.018992 |
| | 0.010878 |

NOTES: S=40 (S = # simulation draws). *** = sign. at the 1% level., ** = sign. at the 5% level., * = sign. at the 10% level.. A full set of time dummies is included into the probability of adoption function