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Innovation, Productivity and Exports: the Case of Hungary

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Innovation, Productivity and Exports: the Case of Hungary

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Abstract

This paper estimates the relationship between innovation and firm performance by using Community Innovation Survey data for Hungary. It exploits the possibility of linking the innovation data to ownership and disaggregated trade data. Innovative firms are more productive, more likely to trade and export into more countries. Foreign firms are more likely to innovate compared to similar domestic firms, but the amount of R&D is a weaker predictor of the innovative output of foreign firms.

Keywords: innovation, TFP, export, CDM-model

JEL: D24, F23, O31

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Innováció, termelékenység és export

Halpern László – Muraközy Balázs

Összefoglaló

Ebben a tanulmányban az innováció és a vállalati teljesítmény közötti kapcsolatot vizsgáljuk a magyar Közösségi Innovációs Felmérés adatai segítségével. Az innovációs adatokat összekötjük a mérlegadatokkal, valamint a vámstatisztikával. Az innovatív vállalatok termelékenyebbek, nagyobb valószínűséggel vesznek részt a külkereskedelemben és több országba exportálnak. A külföldi tulajdonban lévő vállalatok nagyobb arányban folytatnak innovatív tevékenységet, mint a hazai tulajdonban lévők, de a K+F ráfordításuk és az innováció közötti kapcsolat gyengébb.

Tárgyszavak: innováció, TFP, export, CDM-modell

JEL: D24, F23, O31

1. INTRODUCTION

In recent years the innovative behaviour of firms has become an important centre of attention, especially within the EU. While a lot is known about old member states, few results were published on economies of new member states. Besides understanding the innovative process in these economies, however, it is important to shed some light on the possible policy tools which may promote convergence of these countries effectively. Also, the special features of these countries, especially their very open economies and the importance of foreign-owned enterprises, may enable researchers to study questions about the innovative process in general, what is harder to analyse in more developed economies.

In this paper we provide estimates on the relationship between innovation and productivity in Hungary, which are directly comparable with earlier results for developed European economies. We also link the firm-level innovation data to balance sheet and detailed trade data, what allows us to ask novel questions: the relationship between innovation and export performance and the specificities of foreign firms.

This analysis is made possible as a result of the EU-wide harmonized effort, the Community Innovation Survey (CIS). We use firm-level data from the 2004 and 2006 waves of the Hungarian CIS to provide comparable estimates to the Griffith et al (2006) results. Additionally, we link these data with balance sheet and detailed trade data, what makes possible to study the relationship between innovation and different measures of firm performance. Besides productivity, we are able to study the relationship between innovation and trade performance of firms.

With the empirical model we follow a slightly modified version of Crépon et al. (1998). Their method allows corrections for possible biases resulting from selection and simultaneity of innovation and productivity. Similar models are frequently used in the recent literature examining the relationship between innovative inputs, outputs and performance.

To our knowledge, this is the first paper which links innovation to firm performance measured in terms of detailed trade statistics. The results suggest that innovative firms are more likely to export and export more relative to their turnover. Our transaction-level trade data makes possible to decompose firm-level export performance into the extensive (number of export markets and number of export products) and intensive margin (average export volume by product-market). We find that the exceptional export performance of innovative firms is primarily driven by exporting to more markets rather than exporting more products or a larger intensive margin.

Driving forces of innovation and productivity may differ in new member states from more advanced European economies considerably. First, the difference in the distance from the innovative frontier may make different knowledge-acquisition strategies important in these economies, which may lead to a different role of innovation. Second, in the economies of new member states foreign multinationals play a fundamental role both as producers and as knowledge owners. As decisions on innovative activity and technology of these firms are made mainly in their headquarters, their affiliates may behave differently from stand-alone domestic firms.

To shed some light on the role of multinationals in the Hungarian innovation system, we compare the innovative behaviour of domestic- and foreign-owned firms. The main result is that foreign-owned firms spend more on R&D, and are more likely to innovate, but they do not differ significantly from domestic firms in terms of returns to innovation.

This paper contributes to a number of strands in the literature. First, a recent and quickly growing literature analyses innovative behaviour at the firm level. The empirical framework of this literature is the CDM model, published in Crépon et al. (1998). This framework enables the researchers to estimate the structural relationship among R&D, innovation and firm performance in a cross-sectional setting. We describe this model in detail later.

Growing number of papers use the CDM method to estimate the relationship between innovation and productivity by analyzing the Community Innovation Survey. Griffit, Huergo, Mairesse and Peters (2006) - hereinafter GHMP - for example, compares innovative behaviour in four European countries using the CIS: France, Germany, Span and the UK. Their main conclusion is that the environment which drives innovation and productivity in these countries is remarkably similar, with some important differences, especially in the productivity effects of different innovative activities. As GHMP is an important comparative study, we try to follow their method to make our baseline results comparable to their estimates.

There are some methodological differences between our results and those of GHMP. First, in some steps of the estimation procedure they apply instruments which are only available for innovating firms. As a remedy, we apply instruments which are reported by all firms (hampering factors) and compare our results with those of GHMP as we replicate the GHMP specification as well. Second, our data enables us to estimate the relationship between innovation and TFP as well as innovation and labour productivity. Third, we detect serious multicollinearity between instrumented variables for innovation, so in our preferred specification we include only one of those variables into the model.

Robin and Mairesse (2008) reexamines the GHMP results using more recent data for France, and finds more pronounced effects of innovation on productivity, especially if a firm conducts both product and process innovations. A survey of a number of recent papers using innovation data is Hall et al. (2006). On new member states, Damijan et al. (2008) shows on a sample of Slovenian firms that the significance of innovation as a determinant of productivity depends on the estimation method applied.

The CIS data makes possible the analysis of some specific drivers of innovation. Crespi et al. (2008), for example analyses the importance of knowledge flows in terms of innovative behaviour in Italy. Kremp and Mairesse (2004) provides evidence using the French CIS that firm-level knowledge management policies – like promoting a culture of information and knowledge sharing, motivating employees and executives to remain with the firm, forging alliances and partnerships for knowledge acquisition, implementing written knowledge management rules – is associated with higher productivity. Leeuwen et al. (2009) includes ICT use into the knowledge production function, and shows that it is an important determinant of firm-level innovative output together with R&D in the Netherlands.

Second, our results on the relationship between innovation and export performance are related to the new-new trade literature. As innovation and productivity are positively related, trade models analysing the relationship between productivity and export performance is relevant. Melitz (2003) is the workhorse model of this trade theory, in which firms are heterogeneous with respect to their productivity. The model shows elegantly that more productive firms export more, and are able to pay the fixed costs of exporting for more export markets. The empirical regularities of the number of export markets at the firm level are analysed by Eaton et al. (2004). Such a model provides a good framework for process innovation, and predicts that innovative firms may export more to more markets. This relationship works through productivity indirectly.

Multi-product trade models are motivated by the fact that most firms produce more than one product. Bernard et al. (2006) distinguishes between firm-level ability and product-level expertise. The combination of these two determines the firm-product-level productivity. In this framework, process innovation may be interpreted as modifying firm-level ability, leading to greater exports of existing products and export of new products. Product innovation, on the other hand, means raising product-level expertise, which can lead to greater exports of the product.

Product innovation, on the other hand, may lead to improved product quality. Baldwin and Harrigan (2007) and Johnson (2008) build models in which product quality acts as a demand shifter. Firms producing higher quality goods are able to export more to one market, and export to more markets. In these models innovation does not necessarily lead to an increase in measured productivity, and, as a consequence, allows for a more direct link between innovation and export performance.

The outline of this paper is the following. The next section summarizes the data used and the CDM model. Section 3 presents the results on the relationship between innovation and productivity. Section 4 explores the link between innovation and export performance. Section 5 analyses the differences between foreign and domestic owned firms. Section 6 concludes.

2. DATA AND MODEL

DATA

Comparative firm-level analysis of innovative behaviour across EU member states was made possible by the different waves of CIS conducted in EU member states regularly. Questionnaires are harmonized across member states. There are, however, differences in sampling methods, which we correct – following GHMP – by dropping firms with fewer than 20 employees. In this paper we use two waves of the Hungarian CIS: those conducted in 2003 and 2006. The different waves represent innovative activities of firms in the last 3 years, so in our case 2002-2004 and 2004-2006. We pool the two waves and estimate the regressions on this pooled sample in order to make the results more reliable. We include year dummies to control for changes in the level of the dependent variable.[1]

The survey includes a number of variables related to innovative input and output. A constraint of these data is that the majority of questions are only asked from those firms which report positive innovative *output* or R&D. Besides the most important characteristics of the firm, the survey only asks all firms about the factors that impede innovation and whether the firm used formal protection of intellectual property. As a consequence, in the specifications which are run on all firms, one can only use these variables besides industry and firm size.[2]

Continuous R&D engagement is a dummy variable showing whether the firm reported continuous R&D activity during the 3 year period previous to the survey. *R&D intensity* is the log R&D expenditure per employee in the year of the survey (in 2004 and 2006). There are three binary measures of innovative output: *Process innovation, Product innovation and Share of sales with new products.*[3] We also create a fourth dummy variable, showing whether the firm is *Innovative*, that is, whether firm implements either product or process innovation.

In terms of public support, firms report whether they received *local funding, national funding* or *EU funding* during the period under study. Firms report whether *regulation and standards* or *environmental, health and safety aspects* played an important role in their

[1] Estimating the equations separately does not lead to different qualitative results. Also, there is no sign of structural break.

[2] GHMP uses a wider set of variables in the regressions. This may be a consequence of differences in the survey design.

[3] The definition of the variables can be found in Appendix B of Griffith, Huergo, Mairesse and Peters (2006).

innovation decisions. These variables can be interpreted as representing demand pull. The questionnaire investigated extensively the sources of information which played an important role for the firm: *internal sources within enterprise; Universities as source of information; Government as source of information; Suppliers as source of information; Competitors as source of information* and *Consumers as source of information*. All these are binary variables. From the viewpoint of our analysis it is quite unfortunate that these questions are only asked from innovative firms. As a consequence it is not possible to estimate their effect on innovative output.[4]

Factors that hamper innovation are asked from all firms. While these are subjective questions, and as such, can be criticised to be endogenous to some extent. For example being affected by cognitive dissonance after unsuccessful innovation effort they show how decision makers perceive their environment. In spite of it they may be useful instruments of investing into R&D. Hampering factors are classified into four groups: *cost-related factors, knowledge-related factors, market factors* and *reasons not to innovate*. There are 2-4 questions in all groups.[5] Firms can answer whether the effect of each factor was high, medium or low importance or the factor was not experienced. We generate a variable from each group, showing the number of questions the firm rated as high or medium importance. Those firms which did not implement any innovative activity tend to answer that they did not experience any hampering factor what is difficult to separate from those who effectively skipped answering the questions. In order to correct for this, we include a variable, which takes value of 1 when firm answered 'Factor not experienced' for all these questions.

In terms of appropriability conditions, all firms report whether they used *Formal protection* or whether they cooperated in innovation with other entities. Also, firms report factors impeding their innovative efforts. The survey also provides a number of firm and industry controls. First, firms report whether their most significant market is *International*. Second, firms report the number of their employees enabling us to create a set of dummies.[6]

As the Hungarian CIS data can be merged with balance sheet data at the firm level, detailed industry classification of the firm is also available. However, this is not without cost: we lose a large number of observations. We follow GHMP in using a 10-category industry classification based on 2-digit NACE codes[7]. Balance sheet data provides an opportunity to calculate a

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[4] GHMP include these variables when estimating the knowledge production function.

[5] The questions are: Cost: Lack of funds within your enterprise or group, Lack of finance from outside your enterprise, Innovation cost too high; Knowledge: Lack of qualified personnel, Lack of information on technology, Lack of information on markets, Difficulty in finding cooperation partners for innovation; Market: Market dominated by established enterprises, Uncertain demand for innovative goods or services; Reasons not to innovate: No need due to prior innovations, No need because of no demand for innovations.

[6] <50; 50-99, 100-249, 250-999, >999.

[7] Textiles, Wood/paper, Chemicals, Plastic/rubber, Non-metallic, Basic metals, Machinery, Electrical, Vehicles, Not Elsewhere Classified.

number of performance measures. *Labour productivity* is the log sales per employee in the year of the survey.[8] In contrast to work only using the CIS data, this dataset also makes possible to estimate *total factor productivity (TFP)*. For this we apply the Levinsohn-Petrin procedure (Levinsohn and Petrin, 2003), and estimate the TFP for each 2-digit industry separately. For this we do not need the CIS variables, so we use all observations in the balance sheet dataset which is panel data from 1999-2006, with at least 10000 observations per year. This dataset also contains information on ownership structure of the firm. We create a *Foreign ownership* dummy which takes the value of unity for firms with a foreign stake of at least 10 percent. The GHMP paper proxies capital intensity with investment intensity, which is available in the 2000 CIS wave, but not in our CIS data. Balance sheet data, however, contains information on *Capital intensity*, which we include into our regressions.

The balance sheet dataset informs whether a firm *export*s and *export intensity* relative to total turnover can also be calculated what allows analysing performance measures related to exporting. For 2003 (and earlier years) we have detailed trade data at the firm-product-destination level, which include trade volumes and physical quantities.[9] We link this to the 2002-2004 CIS data to decompose export share to its factors. In particular, we generate firm-level variables reflecting the number of trade *destinations*, the number of (6-digit) *products* exported and the *intensive margin*: trade volume divided by the number of destination-product pairs.

Table 1 shows summary statistics of our variables. The two waves of Hungarian CIS refer to 2001-2003 and 2004-2006.

[Table 1 around here]

Some interesting differences deserve mentioning if one compares these statistics with similar statistics from Western-European economies (as reported in Table 2 by GHMP). In terms of innovative inputs, a relatively low number of Hungarian firms conducted R&D continuously: it is about 10 percent in the period under study, compared to nearly 40 % in Germany, 35 % in France, 27% in the UK and 20 % in Spain. Hungarian firms are somewhat less innovative than their counterparts in more developed countries: in 2006, 20.8 % of the firms in the sample implemented a product innovation, and 20.1 % implemented a process innovation. This share is similar to that observed in the UK in 2000, but much lower than what was observed for Germany (42 % and 55 %, respectively). The difference is much larger in terms of innovative sales (for firms which implemented a product innovation), which was around 6 % in Hungary on average, while it was around 30% for Germany, the UK and Spain, and 16% in France. In summary, Hungarian firms allocate significantly less resources for

[8] While this information is reported by the firms in the CIS, the data provided to us only includes size categories. As a consequence, we use the balance sheet data to calculate labour productivity.

[9] More on this dataset in Békés, Harasztosi and Muraközy (2009).

innovation than their counterparts in the countries studied by GHMP, and their innovative output is also lower.

MODEL

In this paper we follow closely the model in GHMP to make our results comparable with their estimates. This model is based on Crépon et al. (1998) and is constructed in four steps: (i) Firms decide on making R&D investment or not; (ii) firms decide on the level of R&D; (iii) R&D is transformed into innovation through the knowledge production function where innovation can be product or process innovation, as reported by the firms in the CIS; (iv) the output production function transform the effect of innovation onto productivity. An important watermark of this approach is the assumption that all firms exert some innovative effort, so after estimating (i) and (ii) on available R&D data it estimates the knowledge production function for all firms in the sample.

This model describes the innovative process in a structural form. It distinguishes between the inputs (R&D) and the output of innovative activity (the reported process or product innovation). The model starts from a decision to conduct R&D, then analyses its effect on innovative output and measuring the relationship between innovative output and productivity. It, however, ignores any possible reverse causation, e.g. that more productive firms have more funds to conduct R&D.

This four-step approach is suggested to solve the problem of unobserved heterogeneity and simultaneity in the data. 'Better' firms are more likely to be more productive, conduct more research and are more likely to innovate. Ignoring this kind of simultaneity may lead to biased estimates, establishing a spurious positive relationship between innovation and productivity or R&D and productivity. Simultaneity can be handled by using instrumental variables instead of the observed innovative effort. As most firm-level datasets of innovation are cross-sectional at the moment – or repeated cross-sections with a relatively small number of observations, as in our case – only such contemporaneous instruments are available.

Another issue is the low number of firms conducting R&D and/or innovation. These firms are those, which can expect the most from innovative activities in expected value terms. As a consequence, the return of their innovative effort is likely to be larger than the average across all firms. Omitting this source of selection would lead to an upward bias in the returns to R&D and innovation. The solution is modelling the selection process explicitly in (i) and correct for selection in (ii). As a consequence, equations (iii) and (iv) can be estimated on the whole sample of manufacturing firms, predicting the relationship between R&D, innovation and productivity for all firms, not only for the innovative ones. This approach then yields estimates which are representative for all firms in the sample.

Equations (i) and (ii) are estimated[10] simultaneously by applying a Heckman-model, in which R&D is the dependent variable to control for selection. The predicted values for R&D are calculated for every firm in the sample from the Heckman-model what corrects for the effect of selection. When identifying the selection process – following GHMP – we exclude firm size from the second step, assuming that it only affects the probability that a firm conducts some R&D, but it is independent from the R&D intensity conditional on conducting R&D. Instead we include industry dummies, a dummy showing whether firm faces international competition and the hampering factor variables into both equations. GHMP also includes demand pull, funding and source variables into the second step. We, however, omit them, as they are not available for non-innovating firms, and including them in the second step only may lead to biased and inconsistent results if they are correlated with the error term in the selection equation, what is rather likely.[11] As a robustness check we re-estimated our model with specification in GHMP and report the results in the Appendix.

The predicted R&D effort is considered as an input in the knowledge production function and innovative output can be product or process innovation as reported by the firm in the CIS. As the measure of innovative activity is a dummy variable, the knowledge production function is estimated by a probit model. We estimate 3 probit models for 3 different measures of innovative output. Besides binary variables for process and product innovation, we construct the *innovator* binary variable reflecting whether the firm has been engaged in product and/or process innovation. The probability of innovation is predicted from this model for all firms.

In the final step, we are interested in the effect of innovation on firm productivity. In this equation, the dependent variable is labour productivity or TFP. The main explanatory variables are the predicted probability of innovation, and the controls are size categories and capital intensity.

There are firms in the CIS data which cannot be linked to the balance sheet data. Consequently we do not have productivity measures and exact (4-digit) industry classification information for all firms. As these variables are not important for estimating the determinants of R&D intensity and innovation, we estimate these equations of the full CIS sample to obtain as precise instruments as possible. In the last step, when estimating the relationship between innovation and productivity, we restrict the sample to those firms which can be linked to the balance sheet data. We have also estimated the full model on the restricted sample – not reported here – which did not change the results.

[10] The formal description of the econometric model can be found in Appendix A of Griffith, Huergo, Mairesse and Peters (2006).

[11] See for deatails in Wooldridge (2002) p.562.

3. RESULTS OF THE CDM MODEL

R&D AND R&D INTENSITY

Table 2 presents our estimates for the R&D intensity equation. This equation is estimated with the Heckman method for sample selection; the first column reports the marginal effects from the selection equation, and the second reports the marginal effects in the second step. The sample includes all firms in the 2004 and 2006 waves of the CIS survey. Contrary to CDM, we only use variables which are asked from all firms; dummies showing whether the firm was engaged in international competition, whether the firm acquires intellectual property rights in the period under study and binary variables reflecting whether the firm considered different innovation impediments important, and a dummy variable showing whether the firm classified any impediment effects important at all. In the Appendix we show that the qualitative results are similar with the variables used by GHMP. We also include a dummy variable for the year of the survey and industry dummies. The excluded variables are the size category dummies. Thus it is assumed that size only affects selection rather than R&D intensity.

International competition and formal protection are important determinants of conducting R&D continuously. These variables are positively related both to conducting R&D and its intensity. Their marginal effects are, however, somewhat lower in Hungary than in the countries analysed by GHMP. Also, industry differences are significant, with the highest probability and intensity in chemicals.

From the hampering factors 'no need for innovation' is the most important, negatively affecting both the probability of R&D and intensity. Managers perceiving no need for innovating are less likely to invest into research and development. This result can be importance for policy; the lack of managerial motivation is more important predictor of the lack of innovation than other factors, what are more directly addressed by innovation policy. As 25 % of Hungarian firms in the CIS indicated that there is no need for innovation, innovation policy may focus on this hampering factor. Naturally it is important to find out to what extent answering 'no need for innovation' is a rationalisation rather than a cause for the lack of innovation.

The other significant impediment factor is the high cost or lack of finance for innovation, which affect R&D intensity but not the probability of conducting R&D. Also, firms not answering questions about the hampering factors are less likely to conduct R&D, reflecting that non-innovative firms are more likely to skip this question. Larger firms are also more likely to conduct R&D.

[Table 2 around here]

KNOWLEDGE PRODUCTION FUNCTION

Table 3 shows the knowledge production function for process and product innovation. The third column reports results for innovation (product and/or process innovation). The estimated model is probit, and marginal effects are reported (at sample mean). The model is estimated for all firms in the CIS sample, including those that did not conduct R&D.

The marginal effect of R&D is precisely estimated but it is significantly smaller than for other countries: doubling R&D effort increases the probability of process and product innovation by 5 and 7 %, respectively. The estimated marginal effect is 1-3 times larger in the Western European economies. This, however, can be a consequence of the much smaller share of innovative firms in Hungary compared to Western Europe (as marginal effects are reported at sample mean). In terms of size, larger firms are more likely to produce process innovation, but it is not true for product innovation. Innovation-hampering factors also lead to lower innovativity. Again, 'no need for innovation' is the most important variable from the hampering factors, having a robust negative coefficient. Market factors also play some role in this model, but the sign of this variable varies across specifications.

[Table 3 around here]

OUTPUT PRODUCTION FUNCTION

Table 4 presents the results for the output production function, i.e. measures of productivity are explained by the instrumented innovation variables, capital intensity (in case of labour productivity), firm size, industry dummies and an ownership dummy to capture the productivity differences between foreign and domestic firms. The sample is restricted to those observations for which the CIS data and the balance sheet data can be matched. The method of estimation is OLS, and we allow the residuals to be heteroskedastic.

The main result in the first and fourth regression is that both innovation measures are significant, but has the opposite sign. This is a sign of multicollinearity, which is not surprising, as the correlation between the two predicted innovation measures is 0.89, while the correlation between the original measures of product and process innovation is 0.44. It seems to be that the estimated knowledge production function is very similar for product and process innovations, suggesting that the instruments are able to predict some common drivers behind the two innovation measures rather than capturing the factors specific to the individual innovation measures. This makes hard to distinguish between the two in the output production function with our sample size.

We propose two solutions for this problem. First, we omit the process innovation measure (which was less important in the GHMP exercise) from the output production function to reduce the extent of multicollinearity. As a result, the coefficient of product innovation is highly significant. The point estimate is 0.17, suggesting that innovative firms are 17 % more productive than similar non-innovative firms. This is very large compared to the results of GHMP, suggesting that innovation is more strongly related to productivity in Hungary than in the comparison countries. Replacing the product innovation variable with process innovation (not reported) yields very similar results, suggesting that the two predicted innovation variables measure very similar characteristics.

The second solution is to replace the two innovation measures with one, which shows whether the firm was *innovative*, i.e. did it implement a process and/or a product innovation. This variable is also highly significant and its point estimate is very similar to the coefficient of product innovation: 0.21. This result reassures the suspicion that only the effect of one of the innovation measures can be meaningfully estimated in the Hungarian dataset.

Capital intensity has a much larger coefficient than those estimated for investment intensity by GHMP for Western European economies. This may be a consequence of the difference between investment- and capital intensity. The inclusion of the less noisy measure in our estimates may also affect the estimated coefficients of the innovation measure. If this is the case, however, then the effect of innovation can be even more important when one can properly control for capital intensity.[12]

As the aim of including capital intensity to a regression which models labour productivity is to proxy total factor productivity, it is appealing to estimate TFP directly from balance sheet data, and replace labour productivity with it as the dependent variable in the output production function. We estimate TFP with the Levinsohn-Petrin procedure separately for 2-digit industries to allow for differences in technology across sectors.[13]

Qualitatively the results are similar to those with labour productivity: multicollinearity plagues the estimates when two innovation measures are included, while it is positive and significant when only one variable is included[14]. The point estimates are, however, larger when the dependent variable is TFP rather than labour productivity. This may suggest that the effect of innovation is even larger when TFP is estimated properly on panel data.[15]

[Table 4 around here]

[12] Unfortunately we do not have measures of investment intensity.

[13] More on the sample and productivity estimation can be found in Békés, Harasztosi and Muraközy (2009).

[14] It is, however significant only at the 10% level in 2006. This may be the consequence of the smaller sample size.

[15] The CDM is a cross-sectional method, but linking it with the balance sheet data enables one to estimate the relationship between innovation and changes in productivity. Our attempt to replace productivity with change in productivity or firm growth in the last step yielded insignificant coefficients. Standard errors in the exercise were very large, suggesting that more variation and longer time dimension are needed to precisely estimate such a model.

4. THE RELATIONSHIP BETWEEN EXPORTING AND INNOVATION

In export-driven economies better export performance is at least as important as an increase in productivity. As a consequence it is essential to understand whether innovation can contribute to export performance. Our aim in this section is to estimate the relationship between innovation and different measures of export market performance. First, we concentrate on variables that can be obtained from the balance sheet: whether the firm is an *exporter* and its *export intensity* relative to its turnover. Second, we generate firm-level variables using the detailed trade dataset. We calculate the number of export *destinations* and the number of exported (6-digit) *products*. These variables belong to the firm-level extensive margin of trade. The *intensive margin* for firm i is calculated as the ratio of firm-level export volume divided by the extensive margin: the number of export destination-exported product combinations. This definition allows us to decompose firm-level export volume to the number of destinations, the number of products and the intensive margin.

Exporter status and export intensity are calculated from the balance sheet data. These data are linked to both waves of the CIS data. Detailed trade data, however, are only available until 2003 (as data collection methodology changed in 2004 because Hungary joined the EU). We link the data for 2003 to the 2004 wave of the CIS representing the 2002-2004 period. The sample size is smaller for the detailed trade data. Moreover, we drop all destination-product combinations with a smaller volume than 2000 USD in order to reduce noise.[16]

We do not need to change the CDM method significantly to analyse export performance and innovation; the dependent variable in the last step should be replaced with the export performance variables. When the dependent variable is the exporter dummy, we estimate a probit model. For the export intensity, what is 0 for non-exporting firms, we estimate a Tobit model.

The first two columns of Table 5 show regressions results with exporting dummy and export intensity as dependent variables. In different specifications we use different innovation variables. The table suggests a robust pattern: both probability of exporting and export share are significantly positively related to the innovative activity of firms. The tobit regressions suggest that innovator firms export 30% more of their turnover than their non-innovating counterparts.

[Table 5 around here]

We now turn to the disaggregation of this export-premium into three margins. Table 6 reports the results for the variables generated from detailed trade data. Innovative firms export to 2.8 more markets on average, suggesting that innovative firms are able to export profitably

[16] Muraközy and Békés (2009) shows that such transactions can behave differently for larger, permanent trade flows.

to more distant and smaller markets.[17] Interestingly, however, innovation is not associated with a larger number of exported products, suggesting that improving existing products – or introducing new varieties within an already exported product class – is a more important effect of innovation than introducing new, relatively distinct products to export markets.

The intensive margin is positive, but insignificant. This, however, does not mean that trade volume of innovative and non-innovative firms are the same on a given market. As innovative firms are more likely to export to more distant and smaller markets and their average turnover per market is the similar to that of non-innovative firms, they should export more to larger and less distant markets.

[Table 6 around here]

These data also enable us to analyse whether innovation affects trade performance indirectly through productivity or directly through, for example, improving the quality of the products. It requires robustness checks; we also reran the regressions in Table 5 and Table 6 with TFP as an additional explanatory variable – not reported. This did not change the estimated coefficients to any significant degree, suggesting that the relationship between innovation and export performance is a direct one. This provides some support that the higher export performance of innovative firms is mainly driven by enhanced product quality rather than by higher productivity.

All in all, our results confirm a strong and important link between innovation and export performance. Innovative firms are more likely to export; they export more and serve more markets. Being able to export to new markets seems to be the major trade-related effect of innovation.

5. THE DIFFERENCE BETWEEN DOMESTIC AND FOREIGN FIRMS

In new EU member states there is a very wide gap between internationally competitive foreign-owned firms and domestic firms which mainly produce for the domestic market. These differences may turn up in their innovative behaviour. We reran our regressions with a control for foreign-owned firms to see differences in different points of the innovation process. The duality between domestic and foreign firms is very important for different policies, as a major aim of innovation policy in new EU member states is helping domestic firms to integrate into the more productive, internationally competitive segment of the economy.

Table 7 provides evidence for difference in innovative behaviour between foreign and domestic firms. Very large discrepancies can be observed in terms of every variable in the table; foreign firms are more likely to conduct R&D, they invest more into R&D, are more likely

[17] The reported results are estimated with OLS, but the estimates are very similar when estimated with Poisson regression.

to be innovators and are more productive than domestic firms. As both innovative input and output are larger for foreign firms, it is not clear from the descriptive statistics alone whether foreign firms only invest more in innovation or they are also able to transform innovative inputs into innovative outputs more effectively.

We include foreign dummy into all equations and also include interaction of the foreign dummy and the R&D measure into the knowledge production function and the interaction of the foreign and innovation dummies in the output production function to explore the innovation efficiency difference. The foreign dummy is 1 if at least 10% of the firm is in foreign hands and 0 otherwise. Note that, as there is no ownership information in the CIS database, we have to restrict the sample in each step to firms which can be found both in the CIS and the balance sheet data. Table 8 presents our results.

[Table 8 around here]

The R&D selection equation (column 1) shows that foreign and domestic firms do not differ significantly in their willingness to conduct R&D. Column 2 suggests that if foreign firms conduct R&D, its intensity is about twice as large as that of similar domestic firms – although this effect is only significant at the 10 % level.

The results in column 3 for the knowledge production function suggest that *ceteris paribus* foreign firms are more likely to innovate; the highly significant point estimate shows that the difference in term of probability is about 7.5 %. The sign of the interaction term is negative, showing somewhat lower return of R&D for foreign firms. This implies that conducting R&D is a weaker predictor of the innovative activity of foreign firms. This may be explained by the fact that foreign firms are more likely to rely on R&D conducted abroad which does not show up in the Hungarian CIS survey.[18]

The output production function shows that foreign firms are more productive, and the return of innovative activity in terms of productivity is similar to domestic firms.

All in all, foreign firms seem to be conducting somewhat more R&D than domestic firms. The strongest result, however, is that foreign firms are more likely to introduce innovations, and the relationship between R&D and innovation is less pronounced in their case, possibly as a result of R&D conducted abroad.

One concern with this approach can be that the relationship between foreign ownership and innovative behaviour differs across sectors. These differences are not necessarily taken up by the set of sectoral dummies in each equation, as the coefficients of R&D intensity or innovation may differ for sectors with different innovation systems. Also, foreign firms may choose sectors they enter selectively, which may lead to estimation problems.

[18] This effect is present when the dependent variable is product innovation or process innovation rather than output innovation variable.

Whether the sector is high-tech may be a good proxy for different sectoral innovation systems. Consequently comparing high-tech and low-tech sectors with each other may show whether the innovative behaviour of foreign firms differ in sectors with different technological regimes. We use the OECD approach to distinguish sectors.[19] This approach classifies sectors into four categories: low-tech, medium low-tech, medium high-tech and high-tech. Table 9 shows the number of innovators and foreign firms by this classification for the firms which can be linked to the balance sheet data. The table shows that the share of innovator firms goes up with the high-tech ladder. While there is a large difference between low-tech, medium-low tech and medium high-tech sectors, firms in medium high-tech sector are actually more innovative than firms in the high-tech sector.[20] The table also suggests systematic differences in foreign entry; foreign firms are more likely to enter more high-tech sectors of the economy. Here, again there is no difference between the medium high-tech and high-tech sectors.

Based on this evidence we distinguish between low- and medium low-tech sectors on the one hand (LOW) and medium high- and high-tech sectors (HIGH) on the other, and run the CDM model separately for the two sets of sectors. Table 10 shows these results. The first and most interesting result is the lack of difference between domestic and foreign firms in the high tech sector. One have to remember, though, that the sample size in case of high-tech sectors is much lower, possibly leading to less significant estimates. But even considering this the very low point estimates of the coefficients suggest that the innovative behaviour of foreign and domestic firms is very similar in these sectors. It is even more surprising that while there is a positive relationship between R&D and innovation, as expected, innovation does not seem to be leading to productivity gains. Probably sectoral fixed effects and time dummies take up all important differences in TFP and innovation is not related in this time window to TFP.

In contrast to high-tech industries, we can observe large difference between foreign and domestic firms in the low-tech sectors. First, foreign firms are slightly more likely to conduct R&D (although it is only significant at the 10 % level). Second, similarly to our estimates on the whole sample, there is a weaker relationship between R&D intensity and innovation for foreign firms, which may be explained by the international nature of their R&D activities. Third, innovations seem to matter more for foreign firms in terms of productivity.

Innovative behaviour of foreign firms seems to be different only in the low-tech sector. Probably, domestic firms with less innovative strategies are more likely to survive in these sectors than in the high-tech industries. In low-tech industries, the relationship between R&D and innovation is weaker for foreign firms, but innovativeness seems to be more closely related to TFP than in case of domestic firms.

[19] We use the Eurostat classification at the 2-digit level. Source: http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/EN/inn_cisl_sm1.htm

[20] The share of innovators should be less than 50% for all sets of sectors making identification possible.

5. SUMMARY AND CONCLUSIONS

The main aim of this paper was to estimate the relationship between innovation and competition for Hungarian firms linking different firm-level databases. We relied on a slightly modified version of Crépon et al. (1998) to control for simultaneity and endogeneity. The exercise showed that the method yields reasonable results for Hungary. Our results are comparable with those of GHMP who compared 4 Western European countries.

Both R&D performing and innovative firms are much less frequent in Hungary than in the comparison countries. We have found a significantly weaker link between R&D and innovative output in Hungary than the estimates of GHMP, suggesting that the role of R&D in producing innovations is somewhat limited in this new member state; other inputs seem to be more important in the knowledge production process. Regarding productivity, on the other hand, the return of innovative activities appears to be very important for Hungarian firms.

As the Hungarian CIS data can be merged with balance sheet data, we could estimate TFP directly from a large firm-level panel dataset, and check the robustness of the results for this change. Estimated results suggest that the return of innovation is even higher if TFP is measured properly, at least in case of Hungary.

Our dataset also enables us to link the CIS data to detailed trade data, and to study the relationship between innovation and export performance. Innovative firms are more likely to export and their export intensity is larger. The decomposition of firm-level exports into the extensive and intensive margins shows that innovation is strongly related to the number of markets an exporting firm serves, and not related to the number of products exported. Average export per product-destination is similar for innovative and non-innovative firms, suggesting a larger export volume for more important trading partners for innovative firms.

Finally, very large gap was quantified between foreign and domestic firms in terms of innovative inputs, outputs and productivity. This analysis suggests some differences in R&D intensity between domestic and foreign firms, but conditional on R&D-intensity foreign firms are more likely to innovate than similar domestic firms. Also, R&D conducted in Hungary is a weaker predictor of innovation for foreign firms as a consequence of their global R&D activity. These important structural differences suggest that different innovation policy approaches may be optimal for the two sets of firms.

REFERENCES

Baldwin, Richard E. and James Harrigan (2007): *Zeros, Quality and Space: Trade Theory and Trade Evidence*, CEPR Discussion Paper No. DP6368

Bernard, Andrew, Stephen Redding, and Peter Schott (2006): *Multiproduct Firms and Trade Liberalization*, mimeo, Dartmouth.

Békés, Gábor, Péter Harasztosi, and Balázs Muraközy (2009): Hungarian Firms in trade: the descriptive statistics, IEHAS, CeFiG.

Crépon, B., E. Duguet, and J. Mairesse (1998): Research, innovation and productivity: an econometric analysis at the firm level, *Economics of Innovation and NewTechnology*, vol. 7, pp. 115-158.

Crespi, Gustavo, Criscuolo, Chiara, Haskel, Jonathan and Slaughter, Matthew J. (2008): Productivity Growth, Knowledge Flows, and Spillovers, NBER Working Paper No. 13959.

Damijan, Joze P., Kostevc, Crt and Rojec, Matija (2008): Innovation and Firms' Productivity Growth in Slovenia: Sensitivity of Results to Sectoral Heterogeneity and to Estimation Method, LICOS Discussion Paper No. 203/2008.

Griffith, Rachel, Elena Huergo, Jacques Mairesse and Bettina Peters (2006): Innovation and Productivity across four European Countries, *Oxford Review of Economic Policy* 2006 22(4) 483-498.

Hall, Bronwyn H. and Jacques Mairesse (2006): EMPIRICAL STUDIES OF INNOVATION IN THE KNOWLEDGE DRIVEN ECONOMY, NBER WP 12320.

Johnson, Robert C. (2007): *Trade Prices with Heterogeneous firms*, Unpublished working paper, Berkeley, available at http://www.crei.cat/news/recpapers08/johnson.pdf

Kremp, Elizabeth and Jacques Mairesse (2004): KNOWLEDGE MANAGEMENT, INNOVATION AND PRODUCTIVITY: A FIRM LEVEL EXPLORATION BASED ON FRENCH MANUFACTURING CIS3 DATA, NBER WP 10237.

van Leeuwen, G, Pierre Mohnen, Michael Polder and Wladimir Raymond (2009): PRODUCTIVITY EFFECTS OF INNOVATION MODES: WORK IN PROGRESS, *Statistics Netherland Working Paper* 4.

Levinsohn, James and Amil Petrin (2003): Estimating Production Functions Using Inputs to Control for Unobservables, *Review of Economic Studies* April pp. 317-342.

Mairesse, J., P. Mohnen and E. Kremp (2009): The importance of R&D and innovation for productivity: a reexamination in light of the 2000 French Innovation Survey, mimeo.

Melitz, Mark J. (2003): *The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity*, Econometrica, Vol. 71, No. 6 pp. 1695-1725

Muraközy. Balázs and Gábor Békés (2009): *Temporary Trade*, IEHAS DP, 2009/9, available at: http://econ.core.hu/file/download/mtdp/MTDP0909.pdf

Peters, B. (2008): Product and process innovation outcome and firm performance, paper presented at the International Atlantic Economic Conference, Warsaw, Poland, April 10 2008, ZEW, Mannheim(D).

Robin, S. and J. Mairesse (2008): Innovation and productivity: a firm-level analysis for French manufacturing and services using CIS3 and CIS4 data (1998-2000 and 2002-2004), working paper.

Table 1

Summary statistics

	HU 2004	HU 2006
Knowledge/innovation		
Continuous R&D engagement	0.106	0.098
R&D intensity (for firms with continuous R&D engagement)	4.848	4.912
Innovator (product and/or process innovation)	0.327	0.317
Process innovation	0.215	0.201
Product innovation	0.224	0.208
Share of sales with new products (firms with product innovation)	0.056	0.047
Public support		
Local funding	0.009	0.007
National funding	0.090	0.078
EU funding	0.015	0.030
Demand pull		
Environmental, health and safety aspects: low importance	0.141	0.146
Environmental, health and safety aspects: medium or high importance	0.042	0.045
Regulations and standards: low importance	0.118	0.116
Regulations and standards: medium or high importance	0.047	0.050
Sources of information		
Internal sources within the enterprise or group	0.158	0.150
Universities as source of information	0.025	0.037
Government as source of information	0.032	0.041
Suppliers as source of information	0.078	0.068
Competitors as source of information	0.060	0.061
Customers as source of information	0.097	0.107
Appropriability conditions		
Formal protection	0.100	0.081
Cooperation	0.161	0.160
Other		
International competition	0.568	0.549
Size: 20–49	0.301	0.315
Size: 50–99	0.155	0.182
Size: 100–249	0.235	0.228
Size: 250–999	0.206	0.165
Size: >999	0.103	0.110
Observations	2828	3686

The summary statistics are from the 2002-2004 and 2004-2006 waves of the CIS.

Table 2

R&D intensity

	(1) Selection		(2) R&D intensity	
International competition	0.036	***	1.407	***
	0.005		0.242	
Formal protection	0.074	***	1.536	***
	0.012		0.230	
Impediment: cost factors	0.001		-0.214	***
	0.002		0.080	
Impediment: lack of knowledge	-0.001		-0.060	
	0.002		0.077	
Impediment: market factors	-0.003		-0.117	
	0.003		0.121	
Impediment: no need	-0.015	***	-0.506	***
	0.003		0.154	
No answer for impediment questions	-0.063	***	-1.520	**
	0.005		0.650	
Size: 50–99	0.011			
	0.007			
Size: 100–249	0.038	***		
	0.008			
Size: 250–999	0.093	***		
	0.013			
Size: >999	0.062	***		
	0.016			
Observations	6514		6514	
Rho			0.849	
W_industry	0.000		0.000	
Log-likelihood			-2330	

Standard errors below coefficients are robust. Reported are marginal effects for the expected value of the R&D intensity conditional on doing R&D. Industry dummies, year dummy are included in both equations. Industry marginal effects are not shown, W reports the p-value of a test of the joint significance. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3

Knowledge production function

	(1) Process	(2) Product	(3) Process or product
Predicted R&D	0.042 ***	0.075 ***	0.072 ***
	0.008	0.008	0.009
Formal protection	0.109 ***	0.125 ***	0.178 ***
	0.026	0.026	0.030
Size: 50–99	0.047 ***	0.000	0.027
	0.017	0.016	0.019
Size: 100–249	0.095 ***	0.051 ***	0.115 ***
	0.016	0.015	0.018
Size: 250–999	0.206 ***	0.125 ***	0.236 ***
	0.020	0.018	0.021
Size: >999	0.145 ***	0.135 ***	0.170 ***
	0.023	0.023	0.025
Impediment: cost factors	0.011 **	0.004	0.008
	0.005	0.005	0.006
Impediment: lack of knowledge	-0.001	0.004	-0.003
	0.004	0.004	0.005
Impediment: market factors	-0.040 ***	0.017 **	-0.025 ***
	0.007	0.007	0.008
Impediment: no need	-0.029 ***	-0.029 ***	-0.047 ***
	0.009	0.009	0.011
No answer for impediments	-0.157 ***	-0.144 ***	-0.226 ***
	0.014	0.014	0.017
Observations	6514	6514	6514
W_industry	0.182	0.00038 2	0.00038 2
Pseudo R^2	0.143	0.195	0.183
Log-likelihood	-2845	-2733	-3207

The equations are probit equations showing whether the firm conducted process innovation, product innovation or either of them.. Standard errors below coefficients are robust. Numbers reported are the marginal effects (at the sample means) from a probit. W_industry reports the p-value of a test of the joint significance of the industry dummies. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 4

Output production function

	Labour productivity			TFP		
Predicted p of process inn.	0.779 ***			0.936 ***		
	0.242			0.233		
Predicted p of product inn.	-0.407 **	0.170 **		-0.446 **	0.250 ***	
	0.193	0.077		0.186	0.076	
Predicted p of innovator			0.211 ***			0.296 ***
			0.073			0.070
Capital intensity	0.309 ***	0.311 ***	0.309 ***			
	0.013	0.013	0.013			
Size: 50–99	-0.085 **	-0.059	-0.064	0.011	0.043	0.036
	0.041	0.040	0.040	0.038	0.037	0.037
Size: 100–249	-0.072 *	-0.039	-0.054	0.157 ***	0.197 ***	0.177 ***
	0.038	0.036	0.037	0.035	0.033	0.034
Size: 250–999	-0.106 **	-0.027	-0.054	0.402 ***	0.498 ***	0.461 ***
	0.049	0.041	0.043	0.046	0.037	0.040
Size: >999	1.199 ***	1.229 ***	1.218 ***	1.711 ***	1.746 ***	1.732 ***
	0.134	0.135	0.134	0.189	0.190	0.189
Foreign 10 per cent	0.412 ***	0.416 ***	0.413 ***	0.335 ***	0.341 ***	0.337 ***
	0.032	0.032	0.032	0.028	0.028	0.028
Constant	0.840 ***	0.846 ***	0.834 ***	-0.971 ***	-0.962 ***	-0.978 ***
	0.031	0.031	0.031	0.025	0.025	0.026
Observations	3644	3644	3644	3560	3560	3560
R-squared	0.373	0.371	0.372	0.254	0.251	0.253

Dependent variables: labour productivity (log sales per employee) and TFP (estimated with the Levinsohn-Petrin method). The sample is resricted to the subsample of firms which can be linked to balance sheet data. Industry dummies are included. Robust standard errors are reported. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5

Innovation and export performance

	Exporter			Export intensity		
Predicted p of innovator	0.773***			0.261***		
	0.049			0.037		
Predicted p of product inn.		0.949***			0.268***	
		0.061			0.039	
Predicted p of process inn.			1.048***			0.331***
			0.069			0.049
Size: 50–99	0.061***	0.072***	0.043*	0.073***	0.078***	0.067***
	0.021	0.020	0.022	0.025	0.025	0.025
Size: 100–249	0.084***	0.107***	0.078***	0.136***	0.149***	0.137***
	0.021	0.020	0.021	0.023	0.022	0.023
Size: 250–999	-0.008	0.043*	-0.038	0.098***	0.121***	0.091***
	0.027	0.024	0.028	0.025	0.024	0.026
Size: >999	-0.693***	-0.697***	-0.700***	-0.685***	-0.677***	-0.687***
	0.033	0.036	0.032	0.062	0.062	0.062
Foreign 10 per cent	0.293***	0.289***	0.293***	0.350***	0.353***	0.351***
	0.015	0.015	0.015	0.015	0.015	0.015
Observations	3759	3759	3759	3759	3759	3759
Log likelihood	-1654	-1633	-1660	-2036	-2038	-2038
Pseudo-R^2	0.311	0.320	0.309	0.299	0.298	0.298

Dependent variables: exporter status and export intensity. The regressions for exporter status are estimated with probit, the export-intensity equations are estimated by tobit model. The sample is resricted to the subsample of firms which can be linked to balance sheet data. Industry dummies are included. Reported are marginal effects at sample mean. Robust standard errors are reported. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 6

Decomposition of the effect of innovation on export performance

	markets		products		extensive		intensive	
Predicted p of innovator	2.793	***	0.291		3.575	***	661.263	
	0.477		0.458		0.817		476.054	
Size: 50–99	0.492	**	0.672	**	1.168	***	-7.407	
	0.205		0.267		0.392		51.568	
Size: 100–249	1.547	***	1.532	***	3.208	***	-31.931	
	0.207		0.267		0.374		95.713	
Size: 250–999	2.453	***	1.654	***	4.440	***	733.799	***
	0.269		0.282		0.464		121.742	
Size: >999	-1.668	***	-2.588	***	-4.515	***	-347.278	**
	0.329		0.279		0.522		166.654	
Foreign 10 per cent	0.065		-0.028		0.191		464.002	***
	0.181		0.183		0.314		113.096	
Constant	1.341	***	3.485	***	3.711	***	-415.265	***
	0.176		0.243		0.340		157.553	
Observations	1392		1392		1392		1392	
R-squared	0.204		0.074		0.174		0.087	

Dependent variables: number of export markets, products exported and the intensive margin at the firm level. The regressions are estimated with OLS. The sample is resricted to exporting firms in the 2004 wave of CIS. The extensive margin is the number of destination-product combinations, and the intensive margin is export volume divided by the extensive margin. Robust standard errors are reported. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 7

Difference between domestic and foreign firms

	2003		2006	
	Domestic	Foreign	Domestic	Foreign
Observation	1671	714	701	457
Share conducting R&D	0.07	0.16	0.12	0.18
R&D intensity, log	-0.34	0.09	-1.14	0.01
Product innovators, share	0.19	0.34	0.23	0.37
Process innovators, share	0.18	0.30	0.24	0.35
Innovators, share	0.26	0.41	0.35	0.48
Log labour productivity	1.04	1.69	1.16	1.79
Log TFP	0.54	1.10	0.68	1.63

The table includes only those firms for which the CIS data can be merged with the balance sheet data.

Table 8.

The effect of ownership

DEPENDENT VARIABLE:	Conducting R&D	R&D intensity	Innovator	TFP
Predicted R&D			0.099 ***	
			0.019	
Predicted innovator				0.267 ***
				0.081
Foreign (10 perc.)	0.008	0.338 *	0.076 ***	0.305 ***
	0.007	0.203	0.028	0.062
Foreign * pred. R&D			-0.050 ***	
			0.015	
Foreign*predicted innovator				0.066
				0.136
International competition	0.029 ***	1.079 ***		
	0.007	0.293		
Formal protection	0.071 ***	1.258 ***	0.186 ***	
	0.014	0.257	0.040	
Impediment: cost factors	-0.001	-0.299 ***	0.026 ***	
	0.003	0.090	0.010	
Impediment: lack of knowledge	-0.002	-0.097	-0.005	
	0.002	0.082	0.007	
Impediment: market factors	-0.003	-0.010	-0.027 **	
	0.004	0.132	0.012	
Impediment: no need	-0.020 ***	-0.562 ***	-0.050 ***	
	0.005	0.176	0.018	
Imnpediments: no answer	-0.072 ***	-1.717 ***	-0.240 ***	
	0.006	0.613	0.031	
Observations	3816	3816	3816	3560
R-squared	.	.	.	0.252
Pseudo-R-squared	.	.	0.191	.
rho	.	0.834	.	.
ll	-1539	-1539	-1983	.

The sample is restricted to firms which can be found both in the CIS and the balance sheet database. Reported are marginal effects. Set of industry and size dummies are included in all regressions, but not reported to save space. Columns (1) and (2) are estimated with Heckman model, Column (3) with probit and (4) with OLS. Robust standard errors are reported. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 9.

Innovators and foreign firms by technical level of sectors

	Non-innovator	Innovator	Share: innovator %
Low-tech	1,774	816	31.51
Medium low-tech	383	264	40.80
Medium-high tech	286	352	55.17
High tech	182	163	47.25

	Domestic	Foreign	Share: foreign %
Low-tech	1,896	694	26.80
Medium low-tech	387	260	40.19
Medium-high tech	331	307	48.12
High tech	180	165	47.83

We use the Eurostat classification at the 2-digit level. Source: http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/EN /inn_cisl_sm1.htm

Table 10.

The difference between high-tech and low-tech sectors

HIGH-TECH								
DEPENDENT VARIABLE:	Conducting R&D		R&D intensity	Innovator		TFP	
Predicted R&D				0.080	***		
				0.022			
Predicted innovator						-0.102	
						0.131	
Foreign 10 per cent	-0.006		0.091	0.058		-0.018	
	0.023		0.251	0.094		0.100	
Foreign * pred. R&D				-0.014			
				0.028			
Foreign*predicted innovator						0.111	
						0.165	
Observations	875		875	875		858	
R-squared	.		.	.		0.223	
Pseudo-R-squared	.		.	0.226		.	
rho	.		0.642	.		.	
ll	-595.3		-595.3	-468.6		.	

LOW-TECH							
DEPENDENT VARIABLE:	Conducting R&D		R&D intensity	Innovator		TFP	
Predicted R&D				0.159	***		
				0.040			
Predicted innovator						0.205	*
						0.110	
Foreign 10 per cent	0.013	*	0.382	0.059		0.275	***
	0.007		0.263	0.043		0.078	
Foreign * pred. R&D				-0.046	**		
				0.023			
Foreign*predicted innovator						0.439	**
						0.195	
Observations	2941		2941	2941		2702	
R-squared	.		.	.		0.280	
Pseudo-R-squared	.		.	0.173		.	
rho	.		0.819	.		.	
ll	-885.1		-885.1	-1489		.	

The sample is restricted to firms which can be found both in the CIS and the balance sheet database. Reported are marginal effects. All variables in the baseline model (table 2-4) are included, but not reported to save space. Columns (1) and (2) are estimated with Heckman model, Column (3) with probit and (4) with OLS. Robust standard errors are reported. * Significant at 10%, ** significant at 5%, *** significant at 1%.

APPENDIX

RESULTS OBTAINED BY USING GHMP APPROACH

There are some differences between our preferred method and that of GHMP. There are some methodological differences between our approach and those of GHMP. First, in some steps of the estimation procedure they apply instruments which are only available for innovating firms. As we find this problematic, we apply instruments which are reported by all firms (hampering factors). Second, our data enables us to estimate the relationship between innovation and TFP as well as innovation and labour productivity. Third, we detect serious multicollinearity between instrumented variables for innovation, so in our preferred specification we include only one of those variables into the model.

We consider our instrumentation strategy more conservative, as the instrument excluded from the second step of the procedure of GHMP may violate the assumptions that these variables should be independent from the error term of the selection equation. We were interested whether our more conservative different instrumentation strategy affected the results in any important way. To check this, we have re-run the model with the instruments in GHMP. Also this makes possible the direct comparison of our results in Hungary to that of GHMP for Western European economies. From the new variables, demand pull factors and national and EU funding are highly significant. As the following table shows, the qualitative results on the key variables are unchanged in a qualitative sense.

The quantitative results are somewhat different, however. Most importantly, the effect of R&D in terms of innovation becomes much higher with these less conservative instruments: it increases from about 0.07 to 0.18. This is much closer to the estimates of GHMP, but it is still significantly lower than those estimated for the Western European economies. The effect of innovation on productivity, however, is surprisingly similar to our earlier estimates. While this shows the robustness of the results, it may also show that the instrumented innovation variable is only slightly affected by the R&D variable, and other characteristics (industry and size) are more important in it.

Table A1.

Estimation results with the instruments of GHMP.

DEPENDENT VARIABLE	Conducting R&D	R&D intensity	Innovator	Labour Productivity	TFP
Predicted R&D			0.177 ***		
			0.014		
Predicted innovator				0.216 ***	0.250 ***
				0.038	0.035
International competition	0.029 ***	1.125 ***			
	0.005	0.257			
Formal protection	0.038 ***	0.903 ***	0.040		
	0.009	0.226	0.033		
Cooperation		0.335 **			
		0.166			
Funding: local	0.005	-0.276			
	0.015	0.450			
Funding: national	0.048 ***	0.819 ***			
	0.011	0.241			
Funding: EU	0.045 ***	1.243 ***			
	0.017	0.322			
Impediments: no answer					
Size: 50–99	0.007		-0.022	-0.031	0.066 *
	0.007		0.022	0.041	0.038
Size: 100–249	0.028 ***		0.042 **	0.020	0.250 ***
	0.007		0.021	0.036	0.032
Size: 250–999	0.063 ***		0.065 ***	0.079 **	0.600 ***
	0.010		0.024	0.038	0.034
Size: >999	0.046 ***		0.117 ***	1.413 ***	1.853 ***
	0.014		0.027	0.141	0.200
Observations	6514	6514	6514	3644	3560
R-squared	.	.	.	0.340	0.224
Pseudo-R-squared	.	.	0.506	.	.
W_demand-pull	.	0.000	0.000	.	
W_sources	.	0.383	0.000	.	.
W_industry	0.000	0.000	0.000	0.000	0.000
Rho	.	0.848	.	.	.
Ll	-2181	-2181	-1938	.	.

The sample is restricted to firms which can be found both in the CIS and the balance sheet database. Marginal effects are reported. Set of industry and size dummies are included in all regressions, and W_industry denotes their joint significance. Similarly, W_sources and W_demand-pull shows the joint significance of source and demand pull variables, respectively (see Table 1 for the variables in these groups). Columns (1) and (2) are estimated with Heckman-model, Column (3) with probit and (4) with OLS. Robust standard errors are reported. *, **, *** significant at 10%, 5%, 1%, respectively.

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