

# What happens when firms patent? New evidence from US economic census data\*

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## Abstract

We build a new concordance between the NBER Patent Data and US Census micro-data, and use it to examine what happens when firms patent. We find strong evidence that increases in patent stock are associated with increases in firm size and scope as well as with changes in factor intensity. We find somewhat weaker evidence that changes in patenting are positively correlated with changes in total factor productivity. We also analyze a sample of first-time patentees, and find significant increases in firm size, scope, and factor intensity subsequent to their first patent application. Evidence for increases in total factor productivity is slightly weaker. Together, these results suggest that patenting is indeed associated with real changes within firms, and in particular that patenting is strongly associated with firm growth through increases in scope. These findings are robust to alternative measures of size, scope and productivity, and to various sample selection criteria.

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# 1 Introduction

Patent statistics have been widely used in studies of firm innovation at least since Scherer (1965). The primary motivator for using these data has been, as Griliches (1990) put it, “the dream of getting hold of an output indicator of inventive activity”. In this context, Griliches poses two fundamental questions (i) what aspects of economic activity do patent statistics actually capture?, and (ii) what would we like them to measure? To answer the first, and as Griliches argues, the potentially more relevant question, it is important to understand the changes that occur within firms when they patent. In this paper, we build and use a new concordance between the NBER Patent Data and firm data at the US Census Bureau (the Bureau) to provide new evidence on this question.

To construct the concordance, we build on the pioneering efforts of Hall, Jaffe and Trajtenberg (2001), and on the Bureau’s extensive investments in developing and maintaining micro-level firm data. Using a detailed set of name-matching procedures, we develop an *annual* link between patent assignees in the NBER Patent Data (constructed by Hall, Jaffe and Trajtenberg, 2001) and firms in the Business Register (previously called the Standard Statistical Establishment List) at the Bureau. This new concordance covers about 48,000 assignees, and about 121,000 assignee-years over 1975 to 1997, representing about two-thirds of all non-individual, non-university, and non-government assignees during this time period.<sup>1</sup>

The comprehensiveness of the Census data allows us to include private firms in our sample, and present a broader picture of patenting in the US manufacturing sector than has been possible using publicly available data.<sup>2</sup> Consistent with prior studies that used smaller samples, we find strong evidence for the highly skewed nature of patenting activity – just 5.5 percent of all manufacturing firms engage in patenting activity. These firms, however, have a disproportionate share of economic activity, accounting for about 59.3 percent of value added, 63.5 percent of capital stock and about 52.2 percent of employment. We find significant heterogeneity across industries in the prevalence of patenting; this is broadly in line with Scherer’s (1983) and Bound et al’s (1984) findings using data on a sample of large and listed US corporations respectively.

Turning to the main question of our study - what happens when firms patent - we find significant overall differences between patent-owning and non-patent owning firms.<sup>3</sup> We study the unconditional group means of four characteristics: size, factor intensity, productivity, and scope. We find that on

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<sup>1</sup>To facilitate the use of our new concordance by researchers, we have compiled a detailed user guide and technical documentation (Balasubramanian and Sivadasan, 2008). This technical note, to be made available to the Bureau, includes a detailed discussion of the benefits and limitations of the new concordance along with the advantages of the existing NBER-Compustat link.

<sup>2</sup>Although the concordance covers all sectors, data access constraints limit the rest of our study to the manufacturing sector.

<sup>3</sup>Throughout, we use terms such as “patent-owning firms” or “patentees” to refer to firms that are matched to one or more patent assignees. While this is line with studies in this literature, note that matching to an assignee does not always imply *ownership*. The patent data do not track re-assignments or sale of patents by firms subsequent to the patents being granted, so that patent ownership is not tracked perfectly.

average, patent-owning firms are much larger (by a factor of about 15 to 16 for output, value added and capital, and about 10 for employment), more skill intensive (by about 13 percent) and more capital intensive (by about 90 percent). Labor productivity of patenting firms is higher by about 52 percent, and TFP differences are about 17 percent (using a Solow residual definition). The gross number of products is higher by a factor of 2.75, and the net number of products by a factor of 2.11.

To understand if these overall differences simply reflect self-selection on pre-existing differences, we investigate two aspects of patenting. First, we examine the within-firm elasticity of firm characteristics to changes in patent stock. We find that the elasticity of size with respect to patent stock is significant (0.156, 0.151, 0.173 and 0.139 log points for output, value added, capital stock and employment respectively). There is also evidence that skill and capital intensity respond positively to patent stock. The elasticity of productivity is smaller, but still significant for both labor productivity and an OLS Firm-Fixed-Effects (OLS-FE) estimate of total factor productivity. Both the gross and net number of products exhibit positive and significant elasticity with respect to patent stock.

We then use data on first-time patentees to examine changes associated with their first patent application. Using specifications that include both firm as well as industry-year fixed effects (which controls for industry-specific age trends), we find that firm size exhibits a significant increase after the first patent application. There is also evidence of an increase in skill and capital intensity, as well as in all productivity measures, following the first patenting event. The gross number of products shows a significant increase; results for net number of products suggest that firms drop some products around the switch. Using an event study approach, we attempt a finer exploration of the timing of these effects. These analyses suggest that there is a significant increase in size and in the gross number of products coincident with the initial patent application. There is also some evidence of increases in factor intensity and labor productivity. Evidence for coincident increases in the TFP measures and in the net number of products is, however, weak.

Together, our results strongly suggest that patenting is associated with real economic effects. These results add to findings from prior studies of patenting and innovation at the firm level (e.g. Griliches, 1981; Pakes, 1985; Austin, 1993; Sakakibara and Branstetter, 2001; Bloom and VanReenen, 2002; Sampath and Ziedonis, 2004; Hall, Jaffe and Trajtenberg, 2005), and support the use of patents as meaningful proxies of firm level innovation. In particular, our results provide strong evidence that patenting is associated with firm growth through the introduction of new products. In addition to the results discussed above, our tests show that sales from new products do indeed account for all of the firm growth observed around the time of first patenting. We also find that the gross number of products increases with patenting even conditional on firm size measures. It may not seem very surprising that patents are associated with introduction of new products, but this relationship has been under-investigated in the literature, particularly using large samples. To our knowledge, this is the first such study using a comprehensive sample. Furthermore, this strong

link between patenting and firm scope confirms the usefulness of patents as measures of new product introductions. The results also suggest that it may be important to consider firm scope (as in e.g. Klette and Kortum, 2004; Bernard Redding and Schott, 2006b; Nocke and Yeaple, 2006) in addition to firm productivity (as in e.g. Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Melitz, 2003) as the source of heterogeneity across firms when modeling patenting behavior.

We undertook a number of other robustness checks of our results. We examined the baseline productivity results and found them to be robust to a variety of modifications of the baseline Cobb-Douglas two-input production function specification. Results of tests using a panel data GMM approach based on Arellano and Bond (1991) and Blundell and Bond (1998), to address potential endogeneity of patent stock and other inputs, were qualitatively consistent with the baseline OLS-FE TFP results. The changes in factor coefficient estimates were in the same direction as observed by Griliches and Mairesse (1995), but the GMM models did not pass one or both of the specification tests.

Our baseline results were also robust to exclusion of outliers, acquisitions, and highly diversified firms. We also examined if there were systematic differences between private and public firms by re-running the baseline regressions separately for these two types of firms. We found the results to be similar for the size and scope variables. For the other variables, the effects were smaller and statistically insignificant in the sample of public firms, which is consistent with that sample being significantly smaller.

Before we turn to the details, we must emphasize that patenting is *not* an exogenous event, so any changes associated with patenting should not be interpreted as being *caused* by patenting. Accordingly, we do not attempt to ascribe any causal interpretation to our results, but rather view them as consistent with patents capturing underlying innovative activity in the firm. Furthermore, we are agnostic about the drivers of innovation, be they external or internal to the firm. We did, however, attempt to rule out contemporaneous industry-wide demand shocks that affect both patenting and firm size.<sup>4</sup> We included detailed 4 digit-industry year effects in all of our specifications as controls for common 4-digit industry year demand shocks. As a robustness check, we used 5-digit industry-year controls, and found the correlation between size and patenting to be robust. As another check, we used lagged patent stocks as instruments for current patent stocks in a panel GMM approach similar to that discussed for productivity above. Although the specifications failed one or both specification tests, the results were broadly consistent with the baseline results. We also checked and found that the size changes around the first patenting event were correlated with commonly used measures of patent quality. While these checks suggest that our results may not be driven by common industry-wide demand shocks that impact all firms, it must be stressed that our results are consistent with latent demand being an important driver of innovation, with only successful innovators being able

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<sup>4</sup>We thank a referee for elucidating this argument and suggesting tests to address this.

to tap into this demand (Schmookler, 1966).

The rest of the paper is organized as follows. The next section (Section 2) briefly discusses the key features and limitations of the new concordance. Section 3 discusses the data, variables and empirical approach used in our study. Section 4 provides descriptive statistics on the economic importance of patent-owning firms. Section 5 presents the overall differences in means between patentees and non-patentees on characteristics such as size, factor intensity, productivity, and scope. Section 6 examines within-firm elasticity of various firm characteristics to patent stock. Section 7 analyzes first-time patentees, and is followed by a discussion of robustness checks in Section 8. Section 9 discusses our findings in the context of related literature, and concludes.

## 2 The NBER Patent Data-Business Register Bridge

This section discusses some key features and limitations of the concordance between the NBER Patent Dataset and the Business Register (BR). Additional details are provided in a user guide and technical documentation intended to accompany the concordance (Balasubramanian and Sivadasan, 2008).

Our concordance has a number of novel features, all of which derive from the Bureau’s extensive investments in the BR. The BR is based on information collected by the Internal Revenue Service and the Bureau, and covers all non-farm employers in the US.<sup>5</sup> Thus, the concordance offers a link to establishments in all non-farm sectors of the economy. Furthermore, it provides a broader coverage of patent assignees than has been possible using publicly available data. Specifically, it extends the linkage of patent data to unlisted firms and facilitates an analysis of their patenting behavior; this has so far been difficult. The more important novelty arises from the dynamic ownership linkages developed and maintained by the Bureau as part of the BR.<sup>6</sup> The Bureau collects ownership information on establishments in each of the quinquennial Economic Censuses. It also undertakes an annual company organization survey (COS), which includes all multi-establishment firms and a sample of single-unit firms to collect information on ownership and corporate structure.<sup>7</sup> The new concordance leverages this information to provide dynamic updating of ownership linkages (albeit subject to some limitations, particularly in inter-Census years). The current link between patent data

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<sup>5</sup>In this project, we used identifiers available in the BR. The Census Bureau has recently constructed a panel dataset of establishments with improved longitudinal linkages called the Longitudinal Business Database (LBD), which is described in detail in Jarmin and Miranda (2002). Our bridge file can be easily linked to the LBD using establishment identifiers common to the BR and LBD, enabling future researchers to exploit the strengths of the LBD. Also, the Census Bureau has recently put together an Integrated Longitudinal Business Database (ILBD) that combines the LBD with information on non-employers. In future work, our methodology for matching assignees to the BR could be extended to cover the non-employer firms in the ILBD.

<sup>6</sup>We thank Manuel Trajtenberg for pointing out the benefits from constructing a dynamic link.

<sup>7</sup>A number of studies have exploited the ownership linkages available at the Census. Papers that have particularly relied on these ownership linkages include McGuckin and Nguyen (1995), Schoar (2003), Bertrand and Mullainathan (2003), Bernard and Jensen (2007), Maksimovic and Phillips (2002), and Hortascu and Syverson (2008).

and Compustat firm data available in the NBER Patent Data was created by manually searching through secondary sources of ownership structure. This involved enormous time and effort, and hence the ownership structure was limited to that in one year - 1989. Linking to the BR allows us to free-ride on the Bureau's work in developing, maintaining and updating ownership links. Our concordance provides an assignee-year match, as opposed to a single assignee-firm match across all years. This year-by-year match permits tracking of any ownership changes among establishments. This appears to be important, as our checks show that patentee establishments are much more likely to change ownership than non-patentee establishments (Table 7, Balasubramanian and Sivadasan, 2008).

The concordance has a few important limitations that should be considered carefully by those using it. The quality of ownership linkages improves significantly in the Census years, as more resources are devoted to the BR in these years, and because the results of the Economic Census provide more ownership-related information than the annual COS (Jarmin and Miranda, 2002). In our work here, we focus on the Census of Manufacturing and hence, use the best quality ownership linkages. The second limitation of the BR is that it does not cover non-employers, and does not uniformly cover zero-employee establishments of multi-unit firms. Thus, patents owned by subsidiaries with no employees may not be captured by the concordance. A third important constraint is that the concordance is restricted to US assignees that are not individuals or governments because the BR does not cover individuals or foreign firms without establishments in the US. Hence, this concordance cannot be used to analyze patenting by these entities. Moreover, the BR does not enable a robust identification of US establishments of foreign firms. Finally, the limitations of name-matching procedures imply that some assignees may not get matched or may have broken longitudinal links. For more details on these limitations and for a discussion of some other limitations, researchers should refer Section 7 of our technical note (Balasubramanian and Sivadasan, 2008).

Besides these limitations, researchers should also consider the distinct strengths of the existing Compustat-Patent Data link. These include the widespread availability of Compustat data, links to executive compensation (and potentially other external) data unavailable within the Bureau, and coverage of foreign subsidiary information in consolidated financial statements in Compustat. However, researchers who have access to Compustat, and also obtain access to the Census data may be able to exploit strengths of both the datasets by using the Compustat-BR Bridge file available at the Census along with our NBER Patent Data-BR Bridge.

We conclude this section with an overview of the coverage obtained in the new concordance (for details, refer to the user guide and technical documentation). Of the 2.92 million patents granted between 1963 and 1999, and belonging to 175,115 assignees, about 40% belonging to about 57,600 assignees were matched at least once to a firm in the BR. Within a more relevant population of patents applied between 1975 and 1997 by US assignees that were not individuals, universities or

government agencies, 90% of patents and 63.7% of assignees (or about 48,000) are matched at least once to a firm in the BR.<sup>8</sup> The coverage of the concordance is largely uniform across technological categories and years with the exception of 1988. We observe a considerable drop in coverage for 1988 because the BR file for multi-unit firms was unavailable. This, however, does not affect our analyses below because we restrict attention to the Census years.

### 3 Data, Variables and Empirical Approach

#### 3.1 Data

In order to create the primary dataset for our analyses, we link the NBER-BR Bridge to data from the five Censuses in '77, '82, '87, '92 and '97. The establishment data are aggregated to the firm level using the firm identifier (CFN or ALPHA) available in the BR. If a firm has establishments in multiple SIC-4 industries, it is assigned to the largest SIC-4 industry as measured by share of firm output. It is important to note that a firm could be matched to multiple assignees in a single year; hence, data from all assignees are used to compute patenting statistics for the firm. For instance, stock variables such as number of patents applied for in the current year are computed as the sum of the number of patents applied for by all assignees matched to the firm in that year. Indicator variables such as whether a firm has applied for a patent at any time till the current year are based on whether the firm is matched to any assignee till that point in time. Throughout, we use *application year* as the baseline.

We focus on the manufacturing sector due to data access limitations. We had access to detailed micro-data only for the manufacturing sector though we had name and address information for all sectors. Although this potentially limits the generalizability of our results to non-manufacturing industries, it is important to note that the bulk of patenting activity occurs within the manufacturing sector (Scherer, 1983). Our checks also show that approximately 70% of patents that were applied in the five Census years and matched to firms in the BR were by manufacturing firms. Not surprisingly, a number of earlier studies have focused on the manufacturing sector or industries within the manufacturing sector (e.g. Hall and Ziedonis, 2001).

We undertake all our analyses using the quinquennial Censuses of Manufacturing (CMF) instead of using data from the Annual Surveys of Manufactures (ASM). The primary reasons for this decision are significantly greater coverage and better data quality in the CMF. More specifically, an important novelty in our work is the inclusion of non-listed firms, which are generally small or medium-sized. The universal coverage of all manufacturing establishments in the CMF allows us to better analyze these firms. In addition, the quality of ownership links is highest for the Census years (Jarmin and

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<sup>8</sup>The NBER Patent Dataset has identifiers for individuals or governments but not for universities. We used a visual inspection of names to identify 430 universities.

Miranda, 2002), so that firm level patent stock and patenting status measures are more accurately defined in these years. Finally, data on firm scope variables, specifically, output product codes for each establishment, are not available in the inter-Census years.

### 3.2 Variables

Appendix 1 provides detailed definitions of each of the variables used in this study. Here, we present an overview of the key variables.

We define two patenting variables - *patent stock* and a *patenting status*. The patent stock measure is a “depreciated patent stock”, defined as the number of depreciated patents, with each patent depreciated at an annual rate of 15% from the patent application year (following Hall, Jaffe and Trajtenberg, 2005). Patenting status is defined as an indicator variable - 1 from the application date of the first patent (conditional on later approval), and 0 before.<sup>9</sup>

We define four sets of firm characteristics: (i) size, (ii) factor intensity, (iii) productivity, and (iv) scope. *Size* is measured using four variables: (a) log output, (b) log value added, (c) log capital stock, and (iv) log employment. Two aspects of *factor intensity* are examined: (a) capital intensity, measured as log capital per employee, and (b) skill intensity, measured as the ratio of white to blue collar workers.

*Productivity* in the baseline case is measured in three different ways: (a) labor productivity, defined as the log output per employee (b) Solow residual, defined using 4-digit industry-level factor share of costs, and (c) the residual from an OLS Firm-Fixed Effects regression of log value added on log capital and log employment. Note that the first measure is influenced by changes in capital intensity. The latter two measures are alternative measures of total factor productivity, and net out changes in inputs. It is important to remember two points when comparing the Solow measure and the OLS-FE measure. One, the Solow residual is a measure of “real sales” productivity because it is defined as change in real sales less changes in the factor-share-weighted materials, capital structures, capital equipment and employment. Thus, the magnitudes of changes in the Solow real sales TFP residual will be lower than the changes in value-added TFP residual in the OLS-FE specification by about 30%.<sup>10</sup> Two, the two measures could differ because different weights on inputs could yield significantly different productivity residuals. Because the key assumption of competitive input and output markets underlying the Solow measure could be violated in the context of patenting, which

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<sup>9</sup>Thus, a company that files for a patent for the first time in 1984 is classified as a non-patentee until 1983, and then classified as a patentee from 1984 onwards (even if the patent is approved only some years later). Patent applications that were filed but never approved were excluded from our patent data, i.e. firms that filed unsuccessful patent applications would be included as non-patentees.

<sup>10</sup>As Rotemberg and Woodford (1995) show, log productivity change in value added terms ( $d\omega^V$ ) is related to log productivity change in gross output terms ( $d\omega$ ) as:  $d\omega^V = \frac{d\omega}{1 - \gamma S_m}$  where  $\gamma$  is returns to scale and  $S_m$  is the share of material in total revenue. The returns to scale is approximately 0.98 and the share of materials is approximately 0.32, so that the adjustment factor is about 0.69 in our data.

grants temporary monopoly rights within product categories, we place greater emphasis on the OLS-FE measure relative to the Solow measure. Another advantage of the one-step OLS-FE approach is that it allows for potential correlation between patent measures and inputs. Alternative measures of productivity, including a GMM approach to controlling for potential endogeneity of inputs and patent measures in the OLS-FE specification, are discussed in section 8.2.

*Firm scope* is measured in two ways: (i) the logarithm of the gross number of products, defined as the sum of the number of products produced by the firm over its lifetime to date and (ii) logarithm of the net number of products, defined as the number of products reported by the firm in the current year.<sup>11</sup> Each distinct seven-digit SIC product code of a firm is classified as a product. Note that the first measure of scope captures all new product additions; the second measure only captures increases in the number of offered products. Thus, if firms drop older products when they introduce new ones (as documented by Bernard, Redding and Schott, 2006a), the second measure may actually show no change or could even decrease with new product additions. Alternative measures of product scope are examined in Section 8.1.

### 3.3 Empirical Approach

Our empirical analysis can be divided into six parts. We begin in Section 4 with some basic statistics on the role of patentees in manufacturing. We then examine cross-sectional differences between patentees and non-patentees in Section 5. To understand if these cross-sectional differences simply reflect selection, we analyze the changes within firms. In the third part of our analysis, in Section 6, we use a fixed effects regression framework to examine the elasticity of firm characteristics to changes in patent stock. To better understand the timing of the effects and to control for contemporaneous changes within the industry, we then examine changes among first time patentees (Section 7). Specifically, in Section 7.1, we do a before-after and difference-in-differences regression analysis of changes in firm characteristics associated with a change in firm patenting status. In Section 7.2, we attempt to obtain a more fine-grained look at the timing of changes using an event-study analysis of the first patenting event. Finally, in Section 8, we perform a number of robustness checks of our results. More details on the empirical methodology used in each of these steps are discussed in the relevant sections below.

## 4 Basic statistics on the role of patentees in manufacturing

We begin by documenting some basic statistics about the importance and extent of patenting in US manufacturing. Table 1 highlights the economic importance of patent-owning firms in the US

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<sup>11</sup>Because data on products are available only for Census years, the measured gross number of products may understate the true gross number of products produced, as we will miss products introduced by firms in inter-Census years and dropped before the next census.

manufacturing sector. The first column provides the proportion of firms within a SIC-2 industry that own a patent at some point between 1963 and 1997. The most striking fact is that on average, only about 5.5% of all firms own patents. Furthermore, in no SIC-2 industry does this proportion exceed 20%. These figures are consistent with the stylized fact that a large fraction of firms report zero or little R&D expenditure (e.g. Cohen and Klepper, 1992), and with the findings in Cohen et al (2000) that patents are not viewed as very effective means of protecting profits from inventions in a majority of manufacturing industries. Another explanation could be that there are fewer innovations in some industries during the period of our sample. Not surprisingly, industries vary in the fraction of patent-owning firms - only about 0.5% of all firms in lumber and wood products (SIC 22) owned patents compared to a little over 17% in Instruments and Related Products (SIC 38).

The next three columns present the share of patent-owning firms in industry value added, capital stock and employment. Even though they form a small fraction of firms by number, patent-owning firms appear to dominate economic activity. In as many as 12 out of the 19 industries, the small number of patent-owning firms account for more than half the industry value added. On average, they account for more than 52% of all employment in manufacturing, and over 63% of all capital stock. Furthermore, even in industries where the share of patent-owning firms is very small, these firms have a significant economic role (e.g. patenting firms account for only 0.5% of all firms in lumber and wood products, but they contribute almost 30% of all value added). In industries such as transportation (SIC 37), chemicals (SIC 28) and instruments (SIC 38), almost nine-tenths of industry value added can be attributed to the relatively few firms that own patents. Another interesting aspect of Table 1 is that patent-owning firms generally account for a larger share of value added than of employment. This is true in almost every SIC-2 industry. Hence, on average, these firms seem to have much greater labor productivity than their non-patentee counterparts.

It is well established that R&D activity is skewed with a major share of activity being concentrated in large firms (e.g. Bound et al, 1984, Cohen and Klepper, 1996). The economic role of patenting firms in each size decile is presented in Figure 1. As expected, the extent of patenting increases with size but the increase is mostly concentrated in the largest size decile. Almost 80% of value added and a little less than 70% of employment in the tenth size decile pertain to patent-owning firms. In contrast, in the ninth size decile (i.e. the second largest size decile), patent-owning firms account for less than 20% of value added and employment. Another point of note in Figure 1 is that even in the largest size class, only about 20% of firms own patents.

Together, Table 1 and Figure 1 confirm that many of the facts previously documented in the literature using smaller datasets hold true in this more comprehensive Census dataset.

## 5 Overall differences between patentees and non-patentees

We now turn to an examination of the overall differences between patentees and non-patentees.

Table 2 presents the group means of the various firm characteristics for patentees and non-patentees. Comparing the simple means of the size variables (columns 1 and 2), it is evident that on average, patentees are much bigger: output is larger by a factor of 15.0, capital stock by a factor of 15.6, and employment by 9.8.<sup>12</sup> These results demonstrate that the size differences between patenting and non-patenting firms are substantial both economically and statistically, and are consistent with the findings in Table 1 that suggest an important economic role for these firms. Patent-owning firms also exhibit higher skill intensity - the white to blue collar worker ratio for these firms is higher by about 13% - and significantly greater use of capital, almost 90% more capital per worker.<sup>13</sup>

Patent-owning firms are also more productive than other firms. The mean (log) output per employee for patent-owning firms is higher by a factor of 1.5. The Solow TFP measure is also higher for patent-owning firms though the magnitude of the difference (17%) is not as high as that for labor productivity.<sup>14</sup> Finally, the gross and net number of products are higher for patentees, by a factor of about 2.8 and 2.1 respectively. Translating the mean of the logs into levels, the patentees have about 5.1 additional products over their lifetime (i.e. in gross terms), and about 2.0 more products offered at any point in time (i.e. in net terms).<sup>15</sup>

Taken together, the statistics in Table 2 suggest that patent-owning firms are very different from their non-patenting counterparts. They are much larger, tend to choose higher levels of skilled labor and capital, exhibit greater productivity, and have a larger number of product offerings than non-patentees. The next sections go beyond these mean differences, and attempt to understand if part of these differences are attributable to changes in patenting within firms.

## 6 Patent stock and firm characteristics

In this section, we examine if changes in patent stock are related to changes in firm characteristics. We use the following fixed effects regression specification:

$$y_{ijt} = \delta s_{ijt} + \eta_i + \mu_{jt} + \epsilon_{ijt} \quad (1)$$

where  $y_{ijt}$  is the characteristic (e.g. log output) for firm  $i$  in period  $t$ ,  $s_{ijt}$  is the log of the depreciated patent stock,  $\eta_i$  refers to firm fixed effects,  $\mu_{jt}$  are four digit industry-year effects and  $\epsilon_{ijt}$  is the residual error term. The above specification is used to examine all variables except the one-step OLS-FE measure of productivity. Hence, for the other measures of productivity, viz. labor productivity

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<sup>12</sup>Note that these variables are logarithms of the original values, and hence the factor, say, for output is computed as  $e^{2.709} = 15.01$ .

<sup>13</sup>In unreported results, we also examined differences in wage rates between patenting and non-patenting firms. We find that patentees pay higher wages, both for production and non-production workers. This is consistent with the use of higher quality and/or skilled workers by patenting firms.

<sup>14</sup>The mean effects on the OLS-FE one step productivity measure are not presented, as most firms do not change patenting status over the sample period, and thus, will not contribute to the coefficient in a firm fixed effects regression.

<sup>15</sup>The mean levels of the number of products (which is different from the mean of the logs) are examined later in Section 8.1.

and the Solow TFP measure, productivity is measured or “derived” in a first step. In the second step, the productivity term is regressed on patent stock in specification 1.

For measuring the impact of changes in patent stock on the OLS-FE measure of productivity, we use the following single-step approach:

$$v_{ijt} = \alpha k_{ijt} + \beta l_{ijt} + \delta s_{ijt} + \eta_i + \mu_{jt} + \epsilon_{ijt} \quad (2)$$

where  $v_{ijt}$  is the log value added,  $k_{ijt}$  is log of the capital stock and  $l_{ijt}$  is the log of employment. This specification is similar to those used in other studies of patenting, e.g. Bloom and Van Reenen (2002). This specification also controls for industry-specific age effects because age effects for firm  $i$  in industry  $j$  in year  $t$  can be decomposed as  $\theta_j Age_{it} = a_i + b_j t$ , which are absorbed by the firms and industry-year fixed effects.<sup>16</sup>

Because specifications 1 and 2 involve two sets of high-dimensional fixed effects (> 2000 industry-year effects and > 5000 firm fixed effects), it was practically infeasible to run these using standard regressions routines. To implement the specifications, we used the methodology and code proposed by Andrews, Shank and Upward (2006).<sup>17</sup> Standard errors were clustered at the industry level to allow for arbitrary within-industry correlation of errors.<sup>18</sup>

The results are summarized in Table 3. The results indicate an economically and statistically significant elasticity of size with respect to patent stock. A 10 percent increase in log patent stock is associated with about a 1.57 percent increase in output, 1.52 percent increase in value added, a 1.73 percent increase in capital stock, and a 1.39 percent increase in employment.

There is a small but statistically significant effect on skill intensity; a 10 percent increase in patent stock is associated with an increase in the ratio of white- to blue-collar workers by 0.02 percent. Capital intensity is also positively correlated with patent stock, though the magnitude of the effect appears small; a 10 percent increase in patent stock is associated with a 0.37 percent increase in capital intensity.

Labor productivity increases by 1.76 percent for a 10 percent increase in patent stock. This is consistent with the results for the output and employment measure; elasticity of output is more than that of employment with the difference being precisely equal to the coefficient in labor productivity.<sup>19</sup>

The TFP measured as the Solow residual shows a very small and insignificant elasticity with respect

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<sup>16</sup>We thank one of the referees for highlighting this point.

<sup>17</sup>This methodology incorporates the grouping algorithm proposed by Abowd, Creedy and Kramarz (2002). Detailed description of some of the procedures in the “felsdsvreg” procedure proposed by Andrews, Shank and Upward (2006) is available in Cornelissen (2008).

<sup>18</sup>As pointed out by a referee, for firms that switch industries, the industry clustering may not capture error correlations within firms. We checked and found our results robust to clustering at the firm level; standard errors were consistently slightly smaller when clustered at the firm level, but the qualitative conclusions (and significance levels) generally remained the same.

<sup>19</sup>Previous versions of the paper used slightly different samples for each of the measures, and hence, the direct elasticities of labor productivity were slightly different from those obtained indirectly from output and employment elasticities.

to patent stock. The one-step OLS-FE specification does show a significant increase; a 10 percent increase in patent stock increases this measure of productivity by 0.15 percent.

Finally, changes in the number of products produced by the firm are positively related to changes in patent stock. A 10 percent increase in patent stock is associated with a 0.35 percent increase in the gross number of products, and a 0.40 percent increase in the net number of products.

To summarize, these analyses strongly suggest that patenting is associated with real changes within firms. The largest impact is on firm size, followed by firm scope. The impact appears to be smaller on productivity and factor intensity.

## 7 Patenting status and firm characteristics: Analysis of first-time patentees

The above analysis suggests that a part of the overall differences between patentees and non-patentees documented in Table 2 are indeed driven by within-firm changes associated with changes in the extent of patenting. However, the analysis in section 6 excludes data on all non-patentees (since the log of patent stock is undefined for these firms), and thus, does not capture any changes associated with a switch in status from being a non-patentee to a patentee. To analyze this transition effect, we examine a sample of first-time patentees who begin as a non-patentee and become a patentee during our sample period. As discussed earlier, we define the switch as happening in the year that the firm first applied for a patent, conditional on the application being subsequently approved.

We use a regression framework to analyze changes before and after patenting (using firm fixed effects), and to examine the difference-in-differences effects relative to other firms in the industry (using firm and industry-year fixed effects).<sup>20</sup> We supplement these analyses with an “event-study” approach that attempts a more fine-grained exploration of the timing of these effects. We define the first-time a firm patents as an “event”, and examine the timing of changes in firm characteristics relative to this “event” date.

### 7.1 Regression analysis of first time patenting

We begin with a “before-after” analysis of the change in firm characteristics that accompany the switch. We use the following specification:

$$y_{ijt} = \gamma_{ba} D_{it} + \eta_i + \epsilon_{ijt} \tag{3}$$

where the variables are as defined in equation 1 above. The coefficient  $\gamma_{ba}$  provides a simple estimate of the changes that accompany the patenting event. For this analysis, the sample is restricted to firms that switch status during our sample period. As with equation 1, the OLS-FE results use a

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<sup>20</sup>While the analysis in Section 6 also has both firm and industry-year fixed effects, all firms in the sample are patentees. Thus, those estimates are not difference-in-differences effects relative to non-patentees.

specification similar to 3, but with log value added as the dependent variable, and labor and capital included on the right hand side.

The results are presented in Table 4A. Column 1 shows results using all available data for the switchers. In column 2, we focus on the short run effects by restricting the sample to 5 years before and after the “switch” year. The results suggest large before-after changes in all four size measures. Consistent with the results in Table 3, the magnitudes of the increase in value added and output are similar (about 0.54 log points in column 2 for the 5-year window around the switch). The increase in capital stock is larger than the increase in output (about 0.70 log points in column 2). In contrast, the jump in employment (about 0.44 log points in column 2) is smaller than the increase in output, and much smaller than the increase in capital. Consistent with these results, there is a significant increase in capital intensity after patenting (about 0.34 log points in column 2), and a small but significant increase in skill intensity too (by about 3.8 percent).

Consistent with the larger increase in output relative to employment, we find a 0.10 log points (see column 2) increase in labor productivity following the switch. The Solow residual measure of productivity shows no significant change around the switch, but the OLS-FE measure shows an increase in TFP of about 7.4% around the switch. As discussed in Section 3, differences in results between OLS-FE and Solow measures could be driven by the different capital and labor coefficients in the two methods. In particular, the results for size variables in Table 4A do not unambiguously show that increases in sales are greater than the increases in all inputs. The similar magnitudes of changes in sales and value added suggest that materials input changed roughly in proportion with sales. Capital input increased more than output while employment increased less than output. Thus, whether TFP increased depends on how capital and employment are weighted in the estimation of TFP, with higher weighting of capital yielding lower TFP estimates. While the ratio of the overall average Solow factor share of labor to capital is similar to the ratio of the estimated OLS-FE coefficients, the discrepancy could be the result of higher weighting of capital in some industries for the Solow measure.<sup>21</sup>

Both measures of scope show significant increases following the first application for patent, with the gross measure exhibiting a higher increase. Around the time of the switch, there is a 0.51 log point change in the gross number of products compared to a 0.22 log point change in the net number of products. The mean log gross number of products in the sample is about 1.7; hence, a 0.5 log point change (say, from 1.4 to 1.9) represents an addition of approximately 2.7 new product (change from 4.0 to 6.7 products). Similarly, the mean net number of products is about 0.95; a change of 0.21 translates to an addition of about 0.6 products in level terms (assuming a change from 0.9 to 1.1 in log terms). These larger changes in gross number of products implies that subsequent to the

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<sup>21</sup>Our checks show that Solow measure and OLS-FE residuals excluding patenting are very highly correlated (correlation coefficient above 0.96), suggesting that small differences in some industries may be the reason for the discrepancy.

transition, patenting firms drop a number of products when they add new products.<sup>22</sup>

An important limitation of specification 3 is that part of the “before-after” effect could be the result of common industry-specific shocks. Also, some of the growth in size could be because of age effects – suppose all surviving firms grow, then older firms could be expected to be of larger size than younger firms. This survivor/age effect could be different for different industries. We control for common industry shocks as well as for industry-specific linear age trends and obtain a “difference-in-differences” estimate of the change in firm characteristics by including industry-year *and* firm-fixed effects as in the following specification:

$$y_{ijt} = \gamma_{did}D_{it} + \eta_i + \mu_{jt} + \epsilon_{ijt} \quad (4)$$

As we noted below equation (2) in Section 1 above, this specification controls for industry-specific linear age trends, as these can be decomposed as  $\theta_j Age_{it} = a_i + b_j t$ , which are absorbed by the firms and industry-year fixed effects. Since we are interested in the changes relative to non-patentees, the sample includes only switching firms and firms that never patent during the sample period. The coefficient  $\gamma_{did}$  then captures the change in patentee characteristics relative to changes in non-patentees in the same 4-digit industry. Importantly, as noted in section 6, including industry-year effects in this specification also controls for all industry-specific age effects. As before, the OLS-FE results use specifications similar to 4, but with log value added as the dependent variable, and labor and capital as the inputs. These specifications involved two high-dimensional fixed effects ( $> 2000$  industry-year effects and  $> 250,000$  firm effects), and were estimated using the “felsesvreg” procedure developed by Andrews, Shank and Upward (2006). Unlike with 1 and 2, the very high number of firm effects made it computationally infeasible to estimate standard errors clustered by industry. Hence, we were constrained to clustering standard errors at the firm level for these regressions.<sup>23</sup>

The results, presented in Table 4B, confirm the findings in Table 4A. All measures of output increase significantly after patenting, including in the window around the switch. The estimated increases in output, value added and capital stock are comparable (about 0.45 log points in column 1 and 0.37 log points in column 2) while the increase in employment is slightly smaller but still large and significant (about 0.40 log points in column 1 and 0.34 log points in column 2).

Both measures of factor intensity also show significant increases. The skill intensity measure shows an increase of 1.9 percentage points after patenting, and a slightly higher 2.2 percentage points around the switch. Consistent with the larger increase in capital relative to employment, the capital intensity measure increases subsequent to patenting (about 0.09 log points in column 1 and

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<sup>22</sup>We thank a referee for the suggestion that led us to examine both the gross and net number of products. As the referee noted, the importance of adding and dropping of products in the manufacturing sector is documented in Bernard, Redding and Schott (2006a).

<sup>23</sup>As an approximate check, we adjusted the standard errors in Table 4B by the ratio of SEs clustered by firm to SEs clustered by industry (the ratio being obtained from Table 4A). All the significance levels remained unchanged, except for column 1 for the Solow residual measure, where the significance dropped to the 10% level.

a slightly lower 0.08 log points around the switch).

Also consistent with the greater increase in output relative to employment, labor productivity increases post-patenting with a slightly lower increase around the switch (0.035 log points) relative to the overall change (0.057 log points). The changes in output, value added, capital and employment suggest that output increased almost in proportion to materials and capital, but greater than employment. Consistent with this, we find a significant increase in the Solow measure real sales productivity by about 2.6 percent overall and about 2.2 percent around the switch. The OLS-FE productivity measure also shows an increase of about 7 percent overall, and of about 4.85 percent around the switch.

The gross number of products shows a significant increase subsequent to patenting. This increase is larger around the switch (column 2), suggesting that industry peers make up some of the difference in the subsequent years. The pattern is similar for net number of products: the overall change (column 1) is insignificant, while there is a significant increase around the switch (column 2). Also, as discussed before, the larger changes in the gross number of products (relative to net number of products) suggests that patenting firms drop products in the post patenting period.

Taken together, the results in this section bolster the findings in section 6. Similar to the within-firm changes associated with increases in patent stock, we observe significant changes associated with a change in patenting status. As before, the strongest effects are on firm size, with the other variables exhibiting smaller changes.

## 7.2 Timing of effects: Event study analysis of first-time patenting

The analyses in the previous section indicate significant changes in firm characteristics subsequent to a change in patenting status. In this section, we attempt a more fine-grained investigation of the timing of changes associated with a change in patenting status using an event study approach.

In particular, for each firm that switches status from non-patentee to patentee, we define a variable, “index”, as the difference between the current year and the first year the assignee applies for a patent.<sup>24</sup> Thus, index takes negative integer values for the years before the firm first applies for a patent, zero in the first year of applying for a patent, and positive integer values subsequent to its first patent application year. Since the number of observations for extreme values of index was small, the variable was censored at -15 on the lower end and at +15 on the upper end. This variable was subsequently used in OLS regressions of the following form:

$$y_{ijt} = \sum_{k=-15}^{15} \beta_k D_{kit} + \epsilon_{it} \quad (5)$$

where  $y_{it}$  is the variable of interest for firm  $i$  in industry  $j$  in period  $t$ , dummy  $D_{kit} = 1$  if “index” =  $k$  for firm  $i$  in year  $t$ . We then plot the  $\beta_k$  coefficients against index to obtain a picture of how

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<sup>24</sup>Note that even though the data we use are from the five-yearly Censuses, the year of patenting is known accurately, as long as the first year of patenting was after 1963.

the dependent variable changes (relative to industry peers) before and after patenting. To focus on the effects of the patenting event over the short to medium horizon, we restrict attention to 7 years before and 7 years after the first patent application (i.e. index values ranging from -7 to +7).

We first undertake a simple before-after analysis, including in the sample only patentee firms. The results from this analysis is presented in Supplementary Appendix Figure A.1. This figure suggests a significant increase in the size variables coincident with the patent application date. There also appears to be an increase in capital and skill intensity around the patent application date, as well as an increase in the labor productivity measure. Consistent with the earlier results, there us also a significant increase in scope around the patenting event.

As discussed in Section 7.1 above, the before-after analysis could be potentially affected by industry-specific shocks, common to both patentees and non-patentees. Another concern is that of survivor bias. The NBER patent database includes only applicants that *successfully* applied for a patent. While we do not specifically select on survival, the successful patentees could be those that are more likely to survive the 2-3 year gap between the application date and grant of the patent. Further, because we restrict attention to switching firms with observations before and after the patenting event, this means that the post-patenting (index  $\geq 0$ ) coefficients in the before-after analysis are estimated based on firms that survive between the pre- and pos-patenting periods.

In Section 7.1, we discussed how inclusion of firm *and* industry-year effects control for age/survivor bias by controlling for industry-specific age trends. However, a further concern could be that the age/survivor effects are more complex. In particular, age effects could be non-linear (e.g. survivors grow faster when they are younger), or the growth of the patentee firms are correlated with their initial size (e.g. surviving firms that are smaller at a younger age grow faster than firms that are born larger). These concerns could bias our results, *if* patent applicants are generally younger and/or inordinately smaller at a younger age.

In order to carefully control for these concerns, we undertake a difference-in-differences analysis relative to a matched nearest neighbor. We assigned each switching firm and a matched non-patentee control firm to a cell, and re-ran specification 5 with cell-year fixed effects. The matched control firm, chosen from among non-patentees in the same 4-digit industry and of the same age as the switching firm, was the one closest in employment size to the switching firm in the data year prior to patenting. For example, firm XYZ in SIC 4-digit industry 2675 that patented in year 1985 was matched to the firm (in the same industry and of the same age as XYZ) which was closest in employment size to XYZ in the closest available data year prior to patenting (i.e., census year 1982). Because we include cell-year fixed effects, index coefficients are estimated using only data from cells that have both a surviving patentee as well as a surviving non-patentee; the dependent variable for cells where the control firm (or the patentee) exit get absorbed by the cell-year effects.<sup>25</sup>

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<sup>25</sup>A note with more detail (including simulation results and computer code) about how the matching procedure with cell-year effects addresses potential survivor bias is available on request from the authors. We also undertook an event-study

The results, presented in Figure 2, are qualitatively similar to the before-after results in Figure A.1. In particular, the size measures show a significant increase in year 0, i.e. in the year in which the firms first apply for a patent. The magnitude of the increase is similar for sales, value added and capital, but somewhat smaller for labor, consistent with the results in previous sections.

The results for skill intensity similar to the patterns for size – there appears to be an increase in the year of patenting. The pattern for capital intensity is less stark with no systematic effect around the patent application year. The productivity graphs are presented in the lower left of Figure 2. There is a jump in labor productivity in the year of patenting, but this is not persistent. There appears to be no systematic change in either of the TFP measures, though there is some evidence of an increase in year 0.

The scope figures show a stark jump in the log gross number of products, but no systematic increase in the net number of products. This is broadly consistent with the results in Table 4B, and suggests that patenting firms retire some products around the time new products are introduced.<sup>26</sup>

Overall, the magnitudes of size changes in Figure 2 as well as qualitative results for skill intensity and gross number of products are similar to that in Column 2 of Table 4B. In contrast to Column 2 of Table 4B, the effects for total factor productivity and capital intensity do not appear significant in Figure 2. The main source of differences between Figure 2 and Table 4B is that by including cell-year fixed effects, in Figure 2 we allow age-effects to vary arbitrarily across age as well as initial size; the specification in Table 4B, on the other hand, controls for linear industry-specific age effects (through the simultaneous inclusion of firm fixed effects and industry-year effects). Consistent with this explanation, simple before-after graphs (presented as Figure A.1 in a supplementary appendix) obtained by running specification 5 without any fixed effects, show effects that are qualitatively and quantitatively similar to the results in Table 4A.<sup>27</sup>

## 8 Robustness checks

We performed a number of checks to examine the robustness of our results. We begin by discussing the results on firm scope in Section 8.1, and then turn to the robustness of productivity results in Section 8.2. Section 8.3 discusses a number of checks to address potential endogeneity from demand shocks. Finally, Section 8.4 includes a discussion of other robustness checks.

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analysis controlling for 4-digit industry-specific age-quintile fixed effects (Supplementary Appendix Figure A.2). These figures confirm that the results from the before-after analysis of Figure A.1 are not driven by (potentially industry-specific) age-related effects. However, by matching on pre-application size, the matched-control procedure in Figure 2 controls also for potential size-dependent growth rates among survivors.

<sup>26</sup>Graphs with confidence intervals are presented in graphs A.3a, A.3b, A.3c and A.3d of a supplementary appendix, available online. They confirm the qualitative conclusions reached above.

<sup>27</sup>The supplementary appendix is available online at [http://webuser.bus.umich.edu/jagadees/papers/patents/appendix\\_tables.pdf](http://webuser.bus.umich.edu/jagadees/papers/patents/appendix_tables.pdf).

## 8.1 Firm scope (new products) analysis

An unsurprising but novel finding of our study is evidence of the introduction of new products around the time of patenting. In this section, we explore this finding in greater detail.

To understand the relationship between patenting and new product introduction, we focus on the changes around the patenting event among first-time patentees. We analyze the contribution of products introduced by these patentees after their first patent application, both before and after (using specification 3) as well as relative to peers in the industry (using specification 4). Results of our analysis are presented in the first three rows of Table 5.

We focus our discussion here on the short term effects in columns 2 and 4. The before-after specifications in column 2 indicate an increase in sales of about \$6.3 million around the switch. Interestingly, sales of old, pre-patenting products decline by about \$1.4 million on average. Thus, all of the increase in total sales comes from a \$7.7 million increase in new, post-patenting products, which more than offsets the decline in sales from older products. The magnitude of the overall increase in sales is smaller in the difference-in-differences estimates in column 4 (about \$4.4 million), but the estimated decline in old products' sales is higher (about \$2.2 million). As before, the increase in new product sales offsets the decrease in old product sales and accounts for all of the change in total sales.

As another check, we used the simple count of the gross and net number of products, instead of their logarithms. These results are presented in fourth and fifth rows of Table 5, and are qualitatively similar to the baseline results.

We also examined the sensitivity of the scope variable results in Tables 3, 4A and 4B to the inclusion of size and factor intensity controls.<sup>28</sup> Note, however, this analysis is largely exploratory. The impact of controlling for size could be ambiguous. On the one hand, patent-related innovations could result in a higher number of products per employee or per unit revenue. On the other hand, patent-related innovations could have a larger impact on size than on scope. For instance, the invention of one "blockbuster product" (e.g. the light bulb) may dramatically increase revenue and employment in the innovating firm, so that conditional on revenue or employment, the number of products could actually decline post-patenting. This effect is particularly likely to be true relative to non-patenting firms that do not introduce such blockbuster products but bring a number of less successful products to the market.

These results are presented in supplementary appendix Table A.1. We find that the elasticity of gross number of products to patent stock is lower in magnitude, but positive and significant even after conditioning on size and factor intensity variables. The before-after and the difference-in-differences effects of first-time patenting show the same pattern with the additional controls: somewhat lower in magnitude but positive and significant. In most cases, the elasticity of the net number of products

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<sup>28</sup>We thank a referee for suggesting this check.

with respect to patent stock is not statistically significant. While the before-after effect is positive and significant, the difference-in-differences results are *negative* and significant once we add size controls. This is consistent with patenting firms introducing new product(s) that generate more per-product revenue than the retired products.

Together, these results support the baseline results, and are consistent with the hypothesis that around the time of patenting, firms introduce new products and drop older products from their product portfolio.

## 8.2 Productivity analysis

### 8.2.1 Alternative OLS-fixed effects specifications

In this section, we examine the robustness of our results regarding total factor productivity. We first examine alternative specifications of the one-step OLS-FE approach. The results are presented in Table 6A, with the baseline results from Tables 3, 4A and 4B presented in column 1 for comparison.

In column 2, we present results using an alternative definition of capital based on a perpetual-inventory method.<sup>29</sup> In column 3, we allow coefficients to differ by blue and white collar labor by splitting employment into these two components. In column 4, we use a second-order translog specification, i.e. in addition to linear terms for capital and employment, we include quadratic terms as well as their cross-product. In column 5, we use log real sales as the dependent variable regressed on log real materials, log capital stock and log employment.

As can be seen from Table 6A, the baseline results are robust to these alternative specifications. The coefficient tends to be somewhat higher in the more flexible translog specification. As expected (see footnote 10), the magnitude of the estimates are smaller but still significant for the real sales specification in column 5.

Finally, in unreported results, we allowed coefficients on inputs to vary by 2-digit industry, and

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<sup>29</sup>This uses data from both the CMF and ASM, and is computed as follows. Separate stocks are computed for buildings (or structures) and machinery. Real capital stock ( $k_t$ ) in any given year, e.g. for machinery, is computed as  $k_t = (1 - d)k_{t-1} + I_{t-1} + R_t$  where  $d$  is an industry-year specific depreciation rate for machinery,  $I$  is the capital investment in machinery (deflated by an industry-year specific investment deflator for the year  $t - 1$ ) and  $R$  is the capitalized value of capital equipment rentals. (We thank John Haltiwanger and Hyowook Chiang for providing us the depreciation rates and rental prices.) Capital investment in machinery also includes investments in all used capital equipment (irrespective of machinery vs. buildings) since the relevant variables are not well populated. The capitalized value of capital equipment rentals is obtained by dividing the rental expenditure by industry-year specific equipment rental prices. This computation is done separately for buildings and machinery. Since establishments are not necessarily observed in their first year of operation, following Bahk and Gort (1993), capital stock in the first year (initial capital stock) is defined to be the book value of the assets at the end of the year deflated by an industry-year specific capital equipment deflator. This is defined separately for buildings and machinery where the decomposition is available. In case such a decomposition of year-end asset values is not available (1973, 1988-91 and 1993-1997), all initial capital stock is assigned to machinery. If an establishment is not observed every year, following Olley and Pakes (1996), gross investment is imputed linearly ( $\tilde{I}_t = 0.5(I_t + I_{t-k})(k - 1)$ ), where  $\tilde{I}_t$  is the imputed investment for period  $t - k + 1$  to  $t - 1$ , and  $I_t$  is the actual observed investment in period  $t$ ).

We did not use this method for the baseline because most firms in our sample were observed only during the Census years, and thus required significant imputations.

the baseline results remained robust.

### 8.2.2 Arellano-Blundell-Bond GMM estimators

Next, we attempted to control for endogeneity of inputs and patent stock in the baseline specification (2) corresponding to the OLS-FE results in Table 3. We used a GMM approach based on Arellano and Bond (1991) and Blundell and Bond (1998). In contrast to industry-year effects used in the baseline Table 3, for reasons of computational feasibility, we used common year effects.<sup>30</sup>

The results are presented in Table 6B; column 1 reports the baseline (Table 3) OLS-FE results. In the “difference” GMM approach proposed by Arellano and Bond (1991), fixed effects are eliminated by first differencing; lagged levels of the right hand side variables are used as instruments for the first differenced variable. In our application, because all the right hand side variables are considered endogenous, lags of order 2 or more are potentially valid instruments. In column 2, we use order 2 lags as instruments for first differences, i.e.  $X_{i,t-2}$  is used to instrument the first difference ( $X_{it} - X_{it-1}$ ), where  $X$  denotes the vector of endogenous variables (capital, employment and patent stock). In column 3, lags of order 2 and 3 are used. Under the “system” GMM approach proposed by Blundell and Bond (1998), the moments in the “difference GMM” approach are augmented by another set of moment conditions (which are valid if a stationarity assumption for initial conditions hold). In particular, equations in levels are also estimated, and the endogenous variables in levels are instrumented using suitably lagged first differences. In column 4, order 2 lags are used, and in column 5, lags of order 3 and 4 are used.

The estimators are implemented using the code developed by Roodman (2007), who provides detailed description of the procedures used in the code. We use the two-step GMM estimator and report Windmeijer (2005) corrected standard errors. Two specification tests are used to check the validity of the GMM approach. First, the underlying identifying assumption that the error term (excluding the fixed effect component) is serially uncorrelated is checked using the test statistic for serial correlation in the differenced error term (developed by Arellano and Bond, 1991). Under the null hypothesis of no serial correlation in the baseline error term, first differences of the error term would not have serial correlation of order 2. Second, when we have more instruments than the number of endogenous variables, we can use the Hansen/Sargan overidentification test to check for joint validity of the instruments.

In Table 6B, the GMM estimates of the elasticity of productivity are qualitatively consistent with the baseline results, and the magnitudes tend to be significantly larger than in the baseline regressions. However, the Hansen/Sargan overidentification test generally fails. In the specification in column 2, which passes the serial correlation specification test, the coefficient on patent stock is insignificant, and the coefficients on the capital and employment variable appear implausibly large.

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<sup>30</sup>We also checked some specifications for robustness to allowing for different coefficients by 2-digit industry, and found the results generally consistent with those presented here.

Capital and labor coefficient estimates generated by the two system GMM specifications (column 4 and 5) are quite close, and appear reasonable. Consistent with the findings in Griliches and Mairesse (1995), the OLS-FE estimates of the capital coefficient appear to be downward biased and the employment coefficient appears to be upward biased, relative to the GMM estimates.<sup>31, 32</sup>

Overall, though the specification tests fail, the larger magnitudes of the GMM estimate of capital and patent stock coefficients suggest that the link between patenting and productivity observed in the OLS-FE specifications is not driven by endogeneity of input variables or patent stocks.

### 8.2.3 Other checks

One source of increase in measured productivity for patentees could be an increase in markups following the introduction of new products. Recall that our TFP measures subtract a weighted average of inputs from deflated real value added. Because the deflator is common across firms in an industry, firms that have a higher price relative to the industry would appear to have higher measured productivity (Klette and Griliches, 1996). To check this, we examined a proxy for markup using the net margin drawn from Aghion et al (2005). We define the net margin for firm  $i$  in year  $t$  as:

$$\text{margin}_{it} = \frac{\text{sales} - \text{materials cost} - \text{labor cost} - \text{financial cost}}{\text{sales}}$$

where financial cost is measured as the product of cost of capital and total assets.<sup>33</sup> We also checked robustness to using value added in the denominator; any differences between the sales and value added measure would indicate if there were potential savings or dissavings on material costs. Results in the supplementary appendix Table A.2 present a mixed picture. The elasticity of margin on sales with respect to patent stock is surprisingly negative (in column 1), suggesting a decline in margins with increase in patent stock. However, the before-after effects estimated in column 2 for first time patentees is positive and significant. The difference-in-differences effects (column 3) are also positive,

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<sup>31</sup>Two points relating to the instrument matrix are noteworthy. One, following the approach proposed in Holtz-Eakin, Newey and Rosen (1988), missing observations are substituted with zeros so that there is no loss of data from missing observations. Two, we “collapse” the instrument matrix as discussed in Roodman (2007), as this significantly improved the computational speed with little effect on the estimated coefficients. Thus, while the full instrument matrix has T-2 columns even when a single lag is used under difference GMM, once the instrument matrix is “collapsed”, the number of columns in the instrument matrix equals the number of lags used in the difference GMM specification, and equals the number of lags + 1 in the system GMM specification. Thus the Hansen/Sargan overidentification test is inapplicable for the single lag difference GMM specification in column 2 (which is just identified), but applicable for the other GMM columns 3, 4 and 5.

<sup>32</sup>In Blundell and Bond (2000), the discussion of the production function assumes errors are AR1 in the annual data, and hence they run specifications using a dynamic (common-factor) specification. Because we use quinquennial data, we assumed zero first-order serial correlation in errors (excluding fixed effects) and used the Cobb-Douglas specification directly. Note that in all specifications for the one-step OLS-FE (one-step) in Table 6B, the error terms pass the serial correlation test. While this test may be invalid given the failure of the overidentification tests, the results are not inconsistent with our assumption of no serial correlation in the error term (net of the fixed effect) in the quinquennial data.

<sup>33</sup>Following Aghion et al. (2005), the cost of capital is assumed to be 0.085 for all firms and time periods. Checks with a range of numbers around 0.085 yielded similar results.

but small and statistically insignificant. With the measure of margin on value added, all effects are positive and significant (columns 4, 5 and 6). Thus, it appears that there may be some, though not conclusive, evidence that higher markups associated with patenting may be driving the observed increases in productivity.<sup>34</sup>

### 8.3 Endogeneity from demand shocks

We are careful not to ascribe a causal interpretation to our results; we interpret them as consistent with patents capturing innovative activity within the firm.

This interpretation could be biased if industry-specific demand shocks cause both the increase in firm size as well as increased patenting activity. Then, the observed association between size and patenting may not be a reflection of innovative activity in the firm but rather of the demand shock.<sup>35</sup> Our baseline specifications in Table 3 and Table 4B include 4-digit industry year effects, so that they control for demand shocks at a detailed level. In this section, we undertake a series of additional tests to check if “demand-pull” explains a significant part of the observed correlation between firm size and patenting.

Before turning to these tests, note that we do not identify the underlying causes of innovation, and hence do not rule out a role for demand (latent or explicit) in spurring innovation. The “demand-pull” channel for innovation was first proposed by Schmookler (1966), and is part of some models of endogenous technological change (e.g. Acemoglu and Linn 2004). It is plausible that an increase in latent or explicit demand for certain products spur innovation by some firms (who also patent), and that these innovating firms grow (relative to non-innovating industry peers) by capturing share through the introduction of new or better products. In this case, the link between patenting and size increases is still meaningful; though they are triggered by the demand shock, the correlation between size changes and changes in patenting truly reflect innovation in the patenting firms. Thus, what we try to rule out below is the effect of demand shocks that affect non-patenting firms as well, not omitted idiosyncratic ability to exploit demand shocks (which we see as synonymous with innovative ability).<sup>36</sup>

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<sup>34</sup>We also attempted to directly examine physical productivity using data on physical quantities produced, which is available in the census data. However, in order to regress physical quantity output on inputs, we needed to restrict attention to firms producing a single product (as input breakdowns for each product are not available). This limits observations to predominantly homogenous product industries (see Foster, Haltiwanger and Syverson, 2008). For these observations, the number of patentees was extremely limited, and hence we were unable to disclose these results. Even using a sample of firms with at least 80% of output in one product code, the sample size was very small. Using an OLS-fixed effects specification as in equation 2 on this sample, we found a positive but insignificant effect on physical productivity (results not disclosed).

<sup>35</sup>We thank a referee for pointing out this interpretation and suggesting many of the checks we use in this section.

<sup>36</sup>For example, lagged patent stock used as instruments in Section 8.3.1 could be correlated with an omitted ability to exploit demand shocks. Also, even detailed industry/location-year effects (in Section 8.3.3) would not control for this idiosyncratic ability to exploit demand shocks.

### 8.3.1 GMM analysis of baseline effects

A popular approach to controlling for the effects of contemporaneous demand shocks is to use the panel GMM (IV) methodology by Arellano and Bond (1991) and Blundell and Bond (1998), as we did in Section 8.2.2 above. As discussed earlier, this methodology uses suitable lags of patent stock levels (or differences) as instruments for patent stock in a differenced (or levels) version of regression specification (1). As lagged patent stocks are unlikely to be correlated with current demand shocks, instrumenting using lags would address potential bias from “demand-pull” innovations.

The results are presented in Table 7A. Output, value added and capital show positive and significant elasticity to patent stock in all specifications with the estimated elasticities much higher than in Table 3. Employment shows implausibly high negative elasticity in the difference GMM specifications, but positive and significant elasticity in the system GMM specifications. However, though most specifications pass the Hansen/Sargan overidentification test, they fail the serial correlation test. The results tentatively suggest that the baseline results about firms size and patenting may not be strongly upward biased by contemporaneous demand shocks. However, given the failure of the specification tests, and the considerable differences between the estimates from the system and difference specifications, we are hesitant to draw strong conclusions from this analysis.<sup>37</sup>

### 8.3.2 Link to patent quality

If the observed increases in size are indeed linked to patenting, it is reasonable to expect a correlation between the magnitude of size increases and the “quality” of the patents. In order to test this, we adopt the same specification as in equation (3), but add an interaction between the patent-ownership dummy and one of two measures of the quality of the first patent(s) filed by the firm. These quality measures use information on future citations received by those patents. Assuming future citations are uncorrelated with current demand shocks, a positive coefficient on the interaction term would suggest that observed changes are driven by real innovation captured by the patent quality measure, rather than being artifacts of unobserved demand shocks.

We considered two measures of quality: (i) log total number of forward citations to the patents; and (ii) average number of citations per patent. The results are presented in Table 7B. For all

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<sup>37</sup>Results for other variables are presented in the supplementary appendix Table A.3. For the other variables too, we find that specifications fail one or both of the specification tests. In brief, we find the following. Skill intensity elasticity is positive but insignificant in the difference specifications, but positive and significant (and considerably higher than in Table 3) in the system specifications. Capital intensity elasticity is positive in all specifications but seems implausibly higher than the baseline (Table 3) results in the difference specifications. Labor productivity elasticity is implausibly higher than baseline effects in the difference specifications, and about 3 times the baseline effects in the system GMM specifications. The Solow residual is negative and insignificant in the difference specifications, but positive and significant under system GMM. The OLS-FE measure, where inputs were also instrumented, is discussed in detail in Section 8.2.2. The elasticity of gross number of products is positive and significant in the difference specifications, and negative and significant in the system GMM specifications. However, both the specification tests are strongly rejected for system GMM. The results are reversed with the net number of products; coefficients are positive for system and negative for difference GMM.

four measures of size, the interaction of the patent-ownership dummy and the quality variable is significantly positive for both measures of patent quality.<sup>38</sup> Thus, size changes associated with initial patenting are correlated with the quality of patents filed. These results are consistent with the interpretation that size changes accompanying patenting are related to innovation at the firm level. It should be noted, however, that this analysis is not conclusive evidence against a role for “demand-pull” innovation. It is possible that larger demand shocks could lead to bigger or higher quality innovations, so that future citations are related to current unobserved demand shocks. The results are also consistent with findings in the literature that citation-weighted patent counts are informative about patent quality (e.g. Hall, Jaffe and Trajtenberg, 2005).

### 8.3.3 Controlling for more specific demand shocks

Our baseline specifications for Table 3 and Table 4B include 4-digit industry-year effects. We performed additional analyses that attempted to control for more disaggregated demand shocks.

First, we disaggregated log output for each firm to the 5-digit industry level, and then regressed this on the patent stock for the firm (analogous to Table 3). Results are in row 1 of supplementary appendix Table A.5. While the coefficient is positive and significant, it is considerably attenuated compared to that in Table 3. The reason for the attenuation could be the inconsistency between the measures on the two sides of the specification. The output measure on the left hand side is disaggregated to the 5-digit level. However, it is not possible to meaningfully disaggregate the firm patent stock by 5-digit industry; so the right hand side is total firm patent stock. Then, if the firm expands in one 5-digit sector following patenting but not in the other 5-digit sectors, we would observe a more attenuated elasticity estimate.<sup>39</sup>

One potential weakness with using 4-digit industry year effects is that, for diversified firms, the 4-digit industry-year effects may not capture shocks to other sub-sectors important to the firm. To address this problem, we restricted our sample to firms where the share of the predominant 4-digit sector is at least 80% of the total output. The results are presented in rows 2 and 3 of supplementary appendix Table A.5. We find the baseline effects are quite robust to restricting attention to this sample.<sup>40</sup>

Finally, we redid the analysis used for results in Table 4B allowing for region (defined as the Standard Metropolitan Statistical area)-2 digit industry-year effects.<sup>41</sup> The results in the last row

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<sup>38</sup>We ran a similar analysis for all variables, which is summarized in Appendix Table A.4. For all variables except capital intensity, the interaction with quality measure (i) are significant. All interactions except capital intensity, labor productivity and net number of products, are significant with measure (ii).

<sup>39</sup>As a concrete example, for a firm operating in four sectors, a 10% increase in one sector’s output following a 10% increase in patent stock would result in an estimate of 0.25, even if the expanding sector had a disproportionate share of total output. If some 5-digit sectors contract while others expand within a firm, the estimated overall effect could be close to zero, even in cases where there is significant overall output growth.

<sup>40</sup>Results from analysis of all variables for the sample of specialized firms are presented in Table A.6. Qualitatively, all the baseline results are robust to this check. Foster et al (2008) use a similar restriction to define specialized firms.

<sup>41</sup>More detailed industry-region effects were computationally infeasible. Also, we explored specifications using 7-digit

of Table A.5 are similar (somewhat larger) than the baseline.

To summarize, while none of the tests in this section provides conclusive evidence, taken together they suggest that contemporaneous demand shocks may not be driving all of the baseline results.

## 8.4 Other robustness checks

In this section, we discuss additional robustness checks we performed. The results are presented in the supplementary appendix.

### 8.4.1 Measurement error from acquisitions

Because all our analysis is at the firm (rather than establishment) level, it is possible that the results for first-time patentees (Section 7) are affected by acquisition of a patent-owning firm by a non-patentee. This could account for the increase in firm size and firm scope contemporaneous with the patenting event.

To check this, we excluded firms that appeared to acquire any firm in a five-year period before and including the year they switched status, and repeated the analysis in Table 4A and 4B. These results are presented in supplementary appendix Table A.7. As a much stricter test, the sample was restricted to firms that remained single-establishment firms throughout the sample period, thus avoiding all potential acquisition related measurement errors. These results are presented in supplementary appendix Table A.8.<sup>42</sup>

We find that the qualitative conclusions as well as the magnitude of the effects are similar to our baseline, suggesting that our results in Section 7 are not biased by measurement errors induced by acquisitions.

### 8.4.2 Comparison of results for public and private firms

An important novelty of our paper is the coverage of private firms, which are typically smaller than publicly listed firms. Thus, it is interesting to compare results using separate sub-samples of public and private firms. We defined a firm to be public in any given year if it was matched to a Compustat firm in the Compustat-BR Bridge. The results corresponding to Tables 3, 4A and 4B for the sample of public (listed) firms are presented in supplementary appendix Table A.9, and for private (unlisted) firms are presented in Table A.10. Not surprisingly, the number of observations is much smaller in the public firm sample, especially for the sub-sample of switching firms (corresponding to specifications

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product code-year effects, but found it computationally infeasible to include these effects along with firm fixed effects.

<sup>42</sup>In an (unreported) test, we dropped switching firms that have more than 5 patents in the year they switch status to patentee. While a large number of initial patents could arise because some firms do apply for more than 5 patents on their first try, this could also arise from a non-patentee firm acquiring a patenting firm that had built up a portfolio of patents over time. We found our results robust to this test.

in Table 4A).<sup>43</sup> Results in column 1 suggest that elasticity of size and firm scope variables with respect to patent stock is in fact somewhat higher for the sample of public firms. However, the factor intensity and productivity results are not significant in this sample.

The before-after results corresponding to Table 4A suggest big increases in size around the patenting event, with the highest increases for capital, output, value added, and employment (in that order). The skill intensity results are not significant but capital intensity shows a big increase. We find large increases in labor productivity and in scope measures (both gross and net number of products) but no increase in the Solow TFP residual measure. The OLS-FE measure is significant overall but not around the switch.

The difference-in-difference results (corresponding to Table 4B) are qualitatively similar to the baseline results for size and scope variables. However, except for size changes for switchers overall, none of the other effects are significant. The results for private firms in Table A.10 are qualitatively and quantitatively much closer to the baseline, which is not surprising as the overall baseline sample is dominated by the private firms. The biggest differences between the private and public sample are in the difference-in-differences estimates around the switch, which are larger in magnitude and consistently of higher statistical significance in the private firm sample.

Overall the differences between the results using the full sample and those using only the sample of public firms are consistent with the smaller sample size of public firms. For the firm size and scope variables, results using the sample of public firms agree with the full sample results but the effects are generally less significant. For the other variables, we do not see any significant changes in the sample of public firms, whereas we find statistically significant changes with the full sample.

These results suggest that using only a sample of public firms would suffice to examine a range of questions; thus our results with the full sample are largely consistent with earlier work undertaken using mostly public firm data (e.g. Bound et al 1984, Scherer 1983). A sample of private firms, however, would be particularly useful to study the growth or other effects of innovation on small and/or young firms.

### 8.4.3 Other checks

Here we discuss a number of additional (unreported) checks of the results that we undertook.

We checked if the results were being driven by a few industries, or a few years by redoing the analysis excluding one SIC 2-digit industry, and one year, at a time – the results were very similar to the baseline specifications. To test for the influence of outliers, we re-ran specifications in Table 3, 4A and 4B excluding the top and bottom 0.5 percentile of the dependent variable. The results were virtually identical for tables 3 and 4B, and qualitatively very similar for 4A (some magnitudes were slightly lower, but the signs and significance levels remained the same).

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<sup>43</sup>Switching of status is much more likely for smaller/younger firms that are less likely to be listed. Also, as work by Kortum and Lerner (2000) suggests, firms may patent at the venture capital stage, prior to listing.

Furthermore, for the sample of switchers, we tested if the distribution of changes in some of the key variables (output, gross number of products and Solow measure of productivity) around the first patenting event was systematically different from the distribution of changes at other points. We used two-sample Wilcoxon rank-sum and two-sample equality of median tests. Consistent with the results in Table 4A, the tests confirmed that the distribution of size jumps around initial patenting stochastically dominates the distribution of size jumps at other points. The same results were obtained for the gross number of products, but not with the Solow productivity measure. These tests provide additional confirmation that a few outliers are not driving the average changes in these variables.

The literature on innovations makes a distinction between “product” innovations and “process” innovations. Thus, it would be interesting to see if patents associated with process and product innovations have different types of effects. Unfortunately, there is no information in the NBER Patent Data that helps directly classify patents into these two categories. Using data on the titles of the patents and a keyword search procedure, we made a rough classification of patents into “process” and “product” patents. Specifically, we defined a “process” patent dummy variable as equal to 1 for patent filings where the term “process” (or various synonyms for process) appeared, and synonyms for “product” did not appear.<sup>44</sup> With this approach, only about 10% of the patents were classified as process patents. We found that almost all of the effects in Table 3 remain unchanged for the sample of product patents, but were smaller in magnitude and statistically insignificant for process patents. Though crude, this check is consistent with the finding in the literature that patents are used more to protect product innovations (Levin et al., 1987).

We also tried to exclude subsidiaries of foreign firms. We were unable to do so because of data issues. We were informed by the Bureau that reliable data on whether an establishment is a subsidiary of a foreign company is not available at this time.

In addition to these statistical tests, a visual inspection of a small sample of single establishment “switching” firms was performed to check if these firms do show an increase in employment in the year of patenting. A majority of these firms exhibited an increase, with a small minority displaying substantial increases. Though not conclusive, this test is also consistent with the results.

## 9 Discussion and conclusion

In this paper, we build a new concordance between the NBER Patent Data and US Census micro-data, and use it to characterize patenting in US manufacturing and examine what changes happen

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<sup>44</sup>The synonyms we used for process included: method, methodology, technique and procedure. The synonyms for product included: apparatus, equipment, machine, device, tool, instrument, gadget and appliance. We also excluded patent filings with phrases “and process”, “and method”, “and technique” and “and procedure” from the definition of “process” patent dummy, as visual inspections suggested that these were often found in apparent new product-related patents.

within firms that patent. In line with prior research (e.g. Scherer 1983, Bound et al 1984), we find considerable heterogeneity across industries in patenting activity. We find that patenting is concentrated among large firms, so that though patenting firms are a small fraction of all firms, they account for a large proportion of economic activity.

Consistent with related work in the literature (e.g. Hall, Jaffe and Trajtenberg 2005, Bloom and Van Reenen, 2002), our analysis strongly suggests that patenting is associated with real, large and statistically significant changes within firms. Our most robust conclusion is that patenting is associated with a significant increase in firm size. We find strong evidence that this growth is associated with the introduction of new products. We also find somewhat weaker evidence that patenting is positively correlated with firm level productivity increases, as well as with increases in capital and skill intensity.

Griliches (1990) proposed that, ideally, we would like patent statistics “to measure and better understand the economic processes that lead to the reduction in the cost of producing existing products and the development of new products and services”. Our results provide strong evidence that patents capture innovation through introduction of new products. We find a strong positive elasticity of gross number of products with respect to patent stock, and observe a considerable increase in the gross number of products for first-time patentees after their first patent application. The results also suggest that relative to non-patentees, first-time patentees generate significantly more sales from new products introduced after their first patent application. As regards productivity, although we find that it is positively associated with patenting in many of our specifications, our productivity measures use deflated output, and can be affected both by changes in markup as well as by reductions in input use. Hence, with the current data, we are unable to distinguish between these two causes of productivity increase, and cannot conclusively answer if patents also capture pure efficiency-enhancing innovations. Taken together with the starker timing effects observed in Section 7.2 for the gross number of products and size variables (compared to productivity), the results tentatively suggest a stronger correlation between patenting and changes in scope than with improvements in productivity. This is also consistent with the findings in Levin et al (1987), who find that patents are viewed as more effective mechanisms for appropriating value from product than from process innovations, and that secrecy was more effective for process innovations.

The finding of an important role for new product introductions in the growth of patenting firms also suggest that features of a recent class of models that explain firm heterogeneity based on differences in firm scope (such as Klette and Kortum, 2004; Bernard, Redding and Schott, 2006b; Nocke and Yeaple, 2006) may be useful in modeling patenting at the firm level. Our results are broadly consistent with the model of innovation presented in Klette and Kortum (2004). In this model, a firm is defined by the portfolio of goods it produces, and it innovates by extending its product line. Innovations are not directly linked to productivity; hence, assuming patents represent success-

ful innovations, the scope (but not necessarily the productivity) of a firm increases coincident with patenting. In this model, the size of the innovative steps is positively related to measured productivity and R&D intensity. Since the arrival rate of innovations (and hence, patenting) is a positive function of R&D intensity, *ex-ante* differences in productivity between patenting and non-patenting firms would be consistent with the model.<sup>45</sup>

A few caveats should be borne in mind while interpreting our results. It is worth reiterating that patenting is an “endogenous” decision; underlying innovation shocks affect both the dependent variables as well as the decision to patent. Hence, our results must not be given a causal interpretation. Rather, we interpret our results as suggesting that patents are meaningful proxies for real innovative activity within firms. Another limitation of our work is the lack of specific information on innovation-related investments by firms prior to patenting.<sup>46</sup> Without good information on the costs, we cannot assess if the increases in size and scope that we document reflect an increase in welfare or even an increase in the value of the firm. Finally, our work does not reveal the underlying drivers of innovation within firms. Although we undertake tests to rule out potential bias from common industry demand shocks, we cannot rule out a role for (latent) demand in driving innovation.

Our analysis in this paper can be extended in a number of ways. An interesting extension would be to examine inter-temporal trends in the impact of patents, especially in the context of regulatory changes (e.g. the establishment of the court of appeals in 1982 or the Hatch-Waxman Act of 1984), the large increase in patent filing in recent years (Kortum and Lerner, 1998), and recent concerns regarding patent thickets (Shapiro, 2001) and patent trolling (Barker, 2005). Examining cross-industry variations in the impact of patenting on size and scope is another interesting extension, as the importance (and prevalence) of patenting varies considerably across industries. More importantly, we hope that our concordance will significantly extend the number of questions that researchers will be able to analyze using the NBER Patent Data, particularly about innovation by small, young and unlisted firms. We have only addressed the first few questions here.

## References

- [1] Abowd, J., R. Creecy, and F. Kramarz. 2002. Computing person and firm effects using linked longitudinal employer-employee data. Technical Report 2002-06, U.S. Census Bureau. <http://lehd.dsd.census.gov/led/library/techpapers/tp-2002-06.pdf>.

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<sup>45</sup>Additional assumptions that not all innovations are patented and that patenting involves a fixed cost but provides some benefits in the form of extra protection for markups may be needed to explain *ex-ante* size and productivity differences between patentees and non-patentees and to explain why not all firms patent.

<sup>46</sup>It is likely that for most firms a significant part of labor and capital resources committed to innovation are captured in the operating expenses reported in the census data. However, we do not have a breakup of the costs incurred by the firms specifically in activities that led to the innovation that was patented. Moreover, data access constraints prevented us from using R&D data. For researchers interested in the R&D data, Kerr and Fu (2006) provide a concordance between Census data and the NSF R&D Survey.

- [2] Acemoglu, D; Linn, J. 2004. Market size in innovation: Theory and evidence from the pharmaceutical industry. *Quarterly Journal of Economics*, 119:3, 1049-1090.
- [3] Aghion, P; Bloom, N; Blundell, R, et al. 2005. Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics*, 120(2), 701-728.
- [4] Andrews, M., T. Schank, and R. Upward. 2006. Practical fixed-effects estimation methods for the three-way error-components model. *Stata Journal* 6: 461-481.
- [5] Austin, D.H. 1993. An event-study approach to measuring innovative output: The case of biotechnology. *American Economic Review*, 83(2), 253-258.
- [6] Arellano, M; Bond, S, 1991, Some tests of specification for panel data - Monte-Carlo evidence and an application to employment equations. *Review of Economic Studies*, 58: 2, 277-297.
- [7] Balasubramanian, N, and J. Sivadasan, 2008. NBER Patent Data-BR Bridge: User Guide and Technical Documentation. Working Paper, Univeristy of Michigan.
- [8] Bahk, B.H. & Gort M. 1993. Decomposing learning-by-doing in new plants, *The Journal of Political Economy*, 101: 561-583.
- [9] Bartelsman, E.J., Becker, R.A. & Gray, W.B. 2000. NBER-CES Manufacturing Industry Database. June 2000.
- [10] Barker, D.G. 2005. Troll or no troll? Policing patent usage with an open post-grant review. *Duke Law and Technology Review*, No 9.
- [11] Bernard, A. B., Jensen, J. B., 2007. Firm structure, multinationals, and manufacturing plant deaths. *Review of Economics and Statistics* 89, 193-204.
- [12] Bernard A.B, Redding S., & Schott, S. 2006a. Multiproduct firms and product switching. Working Paper, Tuck School of Business at Dartmouth, May 2006.
- [13] Bernard A.B, Redding S., & Schott, S. 2006b. Multiproduct firms and trade liberalization. Working Paper, Tuck School of Business at Dartmouth, December 2006.
- [14] Bertrand, M., Mullainathan, S., 2003. Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy* 111, 1043-1075.
- [15] Bloom N. & Van Reenen J. 2002. Patents, Real Options and Firm Performance. *Economic Journal*, 112, pp. C97-C116.
- [16] Blundell R. and S. Bond., 1998, "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics* 87: 115-43.
- [17] Blundell R. and S. Bond.,2000, "GMM estimation with persistent panel data: an application to production functions" *Econometric Reviews*, 19:321-340

- [18] Bound, J., Cummins, C., Griliches, Z., Hall B.H., and Jaffe, A., 1984, “ Who does R&D and who patents?” , in *R&D, Patents and Productivity*, Griliches, Z. ed, Chicago: U. of Chicago Press, 21-54.
- [19] Chiang, H., 2004. Learning by Doing, Worker Turnover, and Productivity Dynamics. University of Maryland, mimeo.
- [20] Cohen, W. M. and Klepper, S., 1992. The Anatomy of Industry Research-and-Development Intensity Distributions. *American Economic Review*, 82(4), 773-779.
- [21] Cohen, W. M. and Klepper, S., 1996. A reprise of size and R&D. *Economic Journal*, 106(437), 925-951.
- [22] Cohen, W. M., Nelson R. R. and Walsh, J.P., 2000. Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not). NBER Working Paper No. 7552.
- [23] Cornelissen, T. 2008. The Stata command felsdvyreg to fit a linear model with two high-dimensional fixed effects. *Stata Journal* 8: 170-189.
- [24] Davis, S., Haltiwanger, J. and Schuh, S., 1996. *Job Creation and Destruction*. Cambridge: MIT Press.
- [25] Ericson, R., and Pakes, A., 1995. Markov-Perfect Industry Dynamics - A Framework for Empirical Work. *Review of Economic Studies* 62, 53-82.
- [26] Foster, L; Haltiwanger, J; Syverson, C. 2008. Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, 98:1, 394-425.
- [27] Griliches, Z. 1981. Market value, R&D and patents, *Economics Letters*, 7, 183-87.
- [28] Griliches, Z., 1990. Patent Statistics as Economic Indicators - A Survey. *Journal of Economic Literature* 28, 1661-1707.
- [29] Griliches, Z. & Mairesse, J. 1995. Production functions: the search for identification. Working paper no. 5067, National Bureau of Economic Research.
- [30] Hall, B.H, Jaffe, A.B. & Trajtenberg, M. 2001. The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools. NBER working paper 8498.
- [31] Hall BH, Jaffe A, Trajtenberg M. 2005. Market value and patent citations. *Rand Journal of Economics*, 36 (1): 16-38.
- [32] Hall, B.H. & Ziedonis R.H. 2001. The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979-1995. *Rand Journal Of Economics* 32(1): 101-128.
- [33] Hopenhayn, H. 1992. Entry, exit and firm dynamics in the long run. *Econometrica*, 60(5): 1127-1150.

- [34] Hortacsu, A., Syverson, C., 2007. Cementing relationships: Vertical integration, foreclosure, productivity, and prices. *Journal of Political Economy* 115, 250-301.
- [35] Holtz-Eakin, D; Newey, W; Rosen, HS. 1988. Estimating vector autoregressions with panel data. *Econometrica*, 56:6, 1371-1395.
- [36] Jarmin, R. S., and Miranda, J. 2002. The Longitudinal Business Database. Working Papers 02-17, Center for Economic Studies, U.S. Census Bureau.
- [37] Jovanovic, B., 1982. Selection and the Evolution of Industry. *Econometrica* 50, 649-670.
- [38] Kerr, W. & Fu, S. 2006. The Industry R&D Survey: Patent Database Link Project. CES Working Paper CES-WP-06-28.
- [39] Klette, TJ; Griliches, Z. 1996. The inconsistency of common scale estimators when output prices are unobserved and endogenous. *Journal of Applied Econometrics*, 11:4, 343-361.
- [40] Klette, T. J. and Kortum, S., 2004. Innovating firms and aggregate innovation. *Journal of Political Economy*, 112(5), 986-1018.
- [41] Kortum, S. and Lerner, J., 1999. What is behind the recent surge in patenting? *Research Policy*, 28(1), 1-22.
- [42] Kortum, S. and Lerner, J., 2000. Assessing the contribution of venture capital to innovation. *Rand Journal of Economics*, 31(4), 674-692.
- [43] Levin, R. C., Klevorick, A. K., Nelson, R. R. and Winter, S. G., 1987. Appropriating the returns from industrial-research and development. *Brookings Papers on Economic Activity* (3), 783-831.
- [44] Levinsohn, J. & Petrin, A., 2003. Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies*, Blackwell Publishing, vol. 70(2), pages 317-341, 04.
- [45] McGuckin, R. H., Nguyen, S. V., 1995. On productivity and plant ownership change - new evidence from the longitudinal research database. *Rand Journal of Economics* 26, 257-276.
- [46] Maksimovic, V., Phillips, G., 2002. Do conglomerate firms allocate resources inefficiently across industries? Theory and evidence. *Journal of Finance* 57, 721-767.
- [47] Melitz, M. J., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6), 1695-1725.
- [48] Nocke, V. and Yeaple, S. 2006. Globalization and Endogenous Firm Scope. NBER Working Paper Number 12322, National Bureau of Economic Research.
- [49] Olley, G.S. & Pakes, A. 1996. The dynamics of productivity in the telecommunication equipment industry. *Econometrica*, 64(6): 1263-1297.
- [50] Pakes, A. 1985. On patents, R&D and the stock market rate of return. *Journal of Political Economy*, 93(2): 390-409.

- [51] Roodman, David. 2006. "How to do xtabond2: An Introduction to "Difference" and "System" GMM in Stata." Center for Global Development Working Paper No 103.
- [52] Rotemberg, J.J. and Woodford, M, 1995, "Dynamic General Equilibrium Models with Imperfectly Competitive Product Markets", *Frontiers of Business Cycle Research* ed. TF Cooley. Princeton: Princeton University Press.
- [53] Sakakibara, M. & Branstetter, L. 2001. Do Stronger Patents Induce More Innovation? Evidence from the 1988 Japanese Patent Law Reforms. *Rand Journal of Economics*, 32(1): 77-100.
- [54] Sampath, B.N., & Ziedonis, A. 2004. Patent Citations and the Economic Value of Patents: A Preliminary Assessment. In *Handbook of Quantitative Science and Technology Research*, Henk Moed, and Wolfgang Glanzel, Ulrich Schmoch, eds., (Kluwer Academic Publishers: Boston, MA).
- [55] Scherer, F. M., 1965. Firm Size, Market-Structure, Opportunity, and the Output of Patented Inventions. *American Economic Review* 55, 1097-1125.
- [56] Scherer, F. M., 1983. The Propensity to Patent. *International Journal of Industrial Organization* 1, 226-37.
- [57] Schmookler, Jacob. 1966. *Invention and Economic Growth* (Cambridge, MA: Harvard University Press).
- [58] Schoar, Antoinette, 2003. The Effect of Diversification on Firm Productivity. *The Journal of Finance*, Vol. 62 (6), 2379-2403.
- [59] Shapiro, C. 2001. Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard Setting. In *Innovation Policy and the Economy*, A. B. Jaffe, J. Lerner and S. Stern eds., vol.1, MIT Press, pp. 119-150.
- [60] Windmeijer, F. 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126:1, 25-51.

## APPENDIX 1: DEFINITIONS OF VARIABLES

### 1) Size measures

- a) *Output*: For any year before 1996, real output is defined as the sum of shipments (deflated using the 4-digit industry shipment deflator in the CES-NBER database developed by Bartelsman, Becker, and Gray, 2000) and the difference between year-beginning and year-ending deflated work in process and deflated finished goods inventories (the year-beginning inventory is deflated using the previous year's industry shipment deflator and year-end inventory is deflated using the current year deflator). Following the LRD documentation, output for industries 2032, 2033, 2035, 2037, 2038, 2085, 2091, 2111, 2121, 2131 and 2141 was defined to be the sum of deflated shipments and the difference between year-beginning and year-ending deflated work in process inventories. Similarly, for industry 3731 output is defined to be the deflated shipments. For years including and after 1996, due to the unavailability of inventory data, output is simply defined to be the deflated shipments.
- b) *Value added*: Real Value Added is defined as the difference between real output and real materials. Real materials are defined as the sum of deflated cost of material purchases, external contract work, fuel and electricity. For the years before 1997, fuel and electricity are deflated using the energy deflator and the others using a materials deflator. Starting 1997, a single materials deflator is used.
- c) *Capital stock*: This study uses the reported year-end assets deflated by an industry-year specific capital equipment deflator developed by CES researchers John Haltiwanger and Hyowook Chiang. This deflator was based on BEA estimates, and Davis, Haltiwanger and Schuh (1996). An alternative definition of capital stock is discussed in Section 8.2.1.
- d) *Employment* is measured as the total number of employees reported by each firm.

### 2) Factor intensity measures

- a) *Capital intensity* is defined as log capital stock per worker (capital stock divided by employment).
- b) *Skill intensity* is defined as the ratio of white to blue collar workers (number of non-production workers divided by the number of production workers).

### 3) Productivity measures

- a) *Labor productivity* is defined as log output divided by employment.
- b) *TFP (Solow residual)* is defined as  $TFP_{it}^{Solow} = y_{it} - \alpha_m m_{it} - \alpha_s s_{it} - \alpha_e e_{it} - \alpha_l l_{it}$ , where  $y_{it}$  is the log of output of firm  $i$  in year  $t$ ,  $m$  is log real materials (see definition of value added above),  $s$  is log of real depreciated capital structure stock,  $e$  is log of real depreciated capital equipment stock, and  $l$  is employment. The elasticities  $\alpha_m$ ,  $\alpha_k$  and  $\alpha_l$  are defined equal to the material share, capital share and labor share of total costs in the 4-digit SIC (1987) industry  $j$  to which firm  $i$  belongs. The factor share measures, as well as the deflators and depreciation rates used to construct the firm specific real

depreciated capital structure and equipment stocks were taken from the NBER productivity database (Bartelsman, Becker and Gray, 2000).

- c) *OLS-FE productivity measure* is defined as the residual from an OLS firm-fixed-effects regression of log real value added on log real depreciated capital stock and log employment. Definition of real value added, real depreciated capital stock and employment are as given in 1b), 1c) and 1d) respectively above.

#### 4) Product scope measures

- a) *Gross number of products* is defined as the total number of distinct 7-digit product codes reported by the firm over its lifetime up to and including the current year.
- b) *Net number of products* is defined as the number of products reported by the firm in the current year.

#### 5) Other key variables

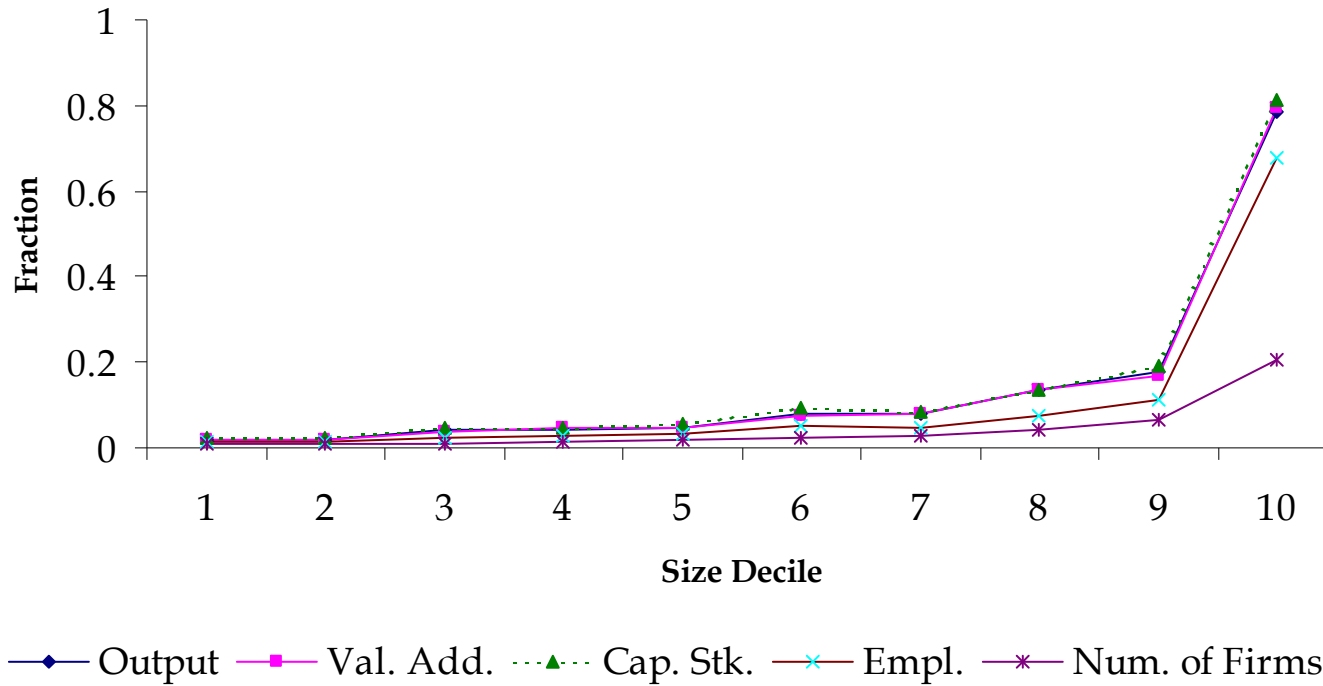
- a) *Depreciated patent stock* is defined as the total of depreciated patents, with each patent depreciated at an annual rate of 15 % (following Hall, Jaffe and Trajtenberg, 2005).
- b) *Industry*: The study adopts 1987 4-digit SIC codes as the basis of industry definition. For most observations before 1997, the “ind” variable provided in the ASM and CM files is used to define the establishment’s primary industry of operation. However, some of the observations wrongly use the 1972 codes, and are corrected per Chiang (2004) who bases these corrections on Davis, Haltiwanger and Schuh (1996). The magnitude and impact of these corrections is very small, though. In addition, establishments with non-existent SIC codes (e.g. 3079) are dropped.

**Table 1: Economic Activity in Manufacturing - Share of Patentees (by Industry)**

<b>SIC</b>	<b>SIC Description</b>	(1) <b>Number of firms</b>	(2) <b>Value Added</b>	(3) <b>Capital Stock</b>	(4) <b>Employment</b>
20	Food and kindred products	1.9%	60.5%	61.7%	48.1%
22	Textile mill products	3.7%	51.5%	56.4%	48.3%
23	Apparel and other textile products	0.9%	26.5%	34.0%	19.5%
24	Lumber and wood products	0.5%	29.4%	37.6%	20.2%
25	Furniture and fixtures	2.7%	42.6%	48.3%	34.3%
26	Paper and allied products	7.1%	77.2%	82.2%	70.6%
27	Printing and publishing	0.5%	33.4%	35.3%	24.4%
28	Chemicals and allied products	9.2%	86.1%	88.1%	79.8%
29	Petroleum and coal products	7.0%	72.4%	84.2%	78.7%
30	Rubber and miscellaneous plastics	7.6%	59.8%	62.9%	51.3%
31	Leather and leather products	3.4%	40.0%	45.7%	33.3%
32	Stone, clay, glass, and concrete products	2.2%	53.8%	56.4%	44.4%
33	Primary metal industries	6.6%	74.2%	80.3%	67.8%
34	Fabricated metal products	5.2%	48.7%	51.5%	41.3%
35	Industrial machinery and equipment	6.8%	72.5%	72.9%	60.5%
36	Electrical and electronic equipment	12.0%	77.4%	77.8%	67.5%
37	Transportation equipment	5.8%	90.3%	90.3%	85.2%
38	Instruments and related products	17.4%	86.8%	89.2%	81.3%
39	Miscellaneous manufacturing industries	3.8%	43.2%	51.2%	35.5%
	<b>ALL INDUSTRIES</b>	<b>5.5%</b>	<b>59.3%</b>	<b>63.5%</b>	<b>52.2%</b>

**Notes:** (i) The numbers represent averages over the period 1977 to 1997. (ii) Due to disclosure restrictions, the statistics for SIC 21 (Tobacco manufactures) have been merged with SIC 20 (Food and kindred products).

Figure 1: Share of Patenting Firms in Manufacturing Activity - By Size Decile



Notes: Size decile 1 is the smallest decile; 10 is the largest size decile.

**Table 2: Mean Firm Characteristics: Patentees vs. Non-patentees**

	Non-Patentees		Patentees		Difference
	Mean	SD	Mean	SD	
<i>Size</i>					
Output	6.199	1.60	8.907	2.14	2.709***
Value added	5.598	1.60	8.311	2.12	2.714***
Capital stock	4.827	1.71	7.575	2.31	2.749***
Employment	2.079	1.41	4.365	1.92	2.286***
<i>Factor intensity</i>					
Skill intensity (White- to blue-collar worker ratio)	0.219	0.19	0.339	0.18	0.120***
Capital intensity (Capital stock per worker)	3.036	1.08	3.680	1.05	0.643***
<i>Productivity</i>					
Labor productivity	4.119	0.69	4.542	0.64	0.423***
TFP (Solow residual)	2.058	0.56	2.216	0.50	0.158***
OLS-FE (one-step) <sup>(iii)</sup>	NA		NA		
<i>Firm Scope</i>					
Net number of products	1.063	0.89	2.078	1.29	1.015***
Gross number of products	0.570	0.68	1.321	1.18	0.750***
Number of observations	1,319,987		66,423		

**Notes:** (i) Patent-ownership is defined as 1 if a firm, which is matched to at least one assignee, has applied for a patent till the current year, 0 otherwise. (ii) All dependent variables, except the white- to blue-collar wage ratio, are logged. (iii) The summary statistics for OLS-FE variable is omitted as the firm fixed effects absorbs the means for most patentees and non-patentees. (iv) \* indicates significance at 10%, \*\* indicates significance at 5%. \*\*\* indicates significance at 1%.

**Table 3: Elasticity of Firm Characteristics to Patent Stock**

	Coeff	(SE)
<i>Size</i>		
Output	0.15662***	(0.00844)
Value added	0.15194***	(0.00873)
Capital stock	0.17340***	(0.00973)
Employment	0.13900***	(0.00758)
<i>Factor intensity</i>		
Skill intensity (White- to blue-collar worker ratio)	0.00248**	(0.00119)
Capital intensity (Capital stock per worker)	0.03772***	(0.00617)
<i>Productivity</i>		
Labor productivity	0.01762***	(0.00330)
TFP (Solow residual)	0.00352	(0.00260)
OLS-FE (one-step)	0.01516***	(0.00413)
<i>Scope</i>		
Gross number of products	0.03561***	(0.00354)
Net number of products	0.04366***	(0.00588)
Number of observations	66,423	

**Notes:** (i) This table reports coefficients on log depreciated patent stock. All dependent variables, except the white- to blue-collar wage ratio, are logged. (ii) All regressions include firm fixed effects as well as 4-digit industry-year effects. (iii) Robust standard errors clustered at the 4-digit industry level are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%. \*\*\* indicates significance at 1%.

**Table 4A: Patenting and Firm Characteristics: Before-after Effects**

	(1)		(2)	
	Switchers overall		Around the Switch	
<i>Size</i>				
Output	0.77094***	(0.03885)	0.54074***	(0.03977)
Value added	0.78273***	(0.04321)	0.54607***	(0.04296)
Capital stock	1.04167***	(0.03066)	0.70520***	(0.03412)
Employment	0.57534***	(0.02612)	0.43893***	(0.02857)
<i>Factor intensity</i>				
Skill intensity (White- to blue-collar worker ratio)	0.05057***	(0.00343)	0.03844***	(0.00391)
Capital intensity (Capital stock per worker)	0.56193***	(0.02763)	0.34257***	(0.02515)
<i>Productivity</i>				
Labor productivity	0.19561***	(0.02008)	0.10181***	(0.01858)
TFP (Solow residual)	-0.00565	(0.01907)	0.00039	(0.01469)
OLS-FE (one-step)	0.11319***	(0.01994)	0.07398***	(0.01985)
<i>Scope</i>				
Gross number of products	0.78727***	(0.01539)	0.51138***	(0.01249)
Net number of products	0.33172***	(0.01228)	0.21792***	(0.01560)
Number of observations	31,336		15,382	

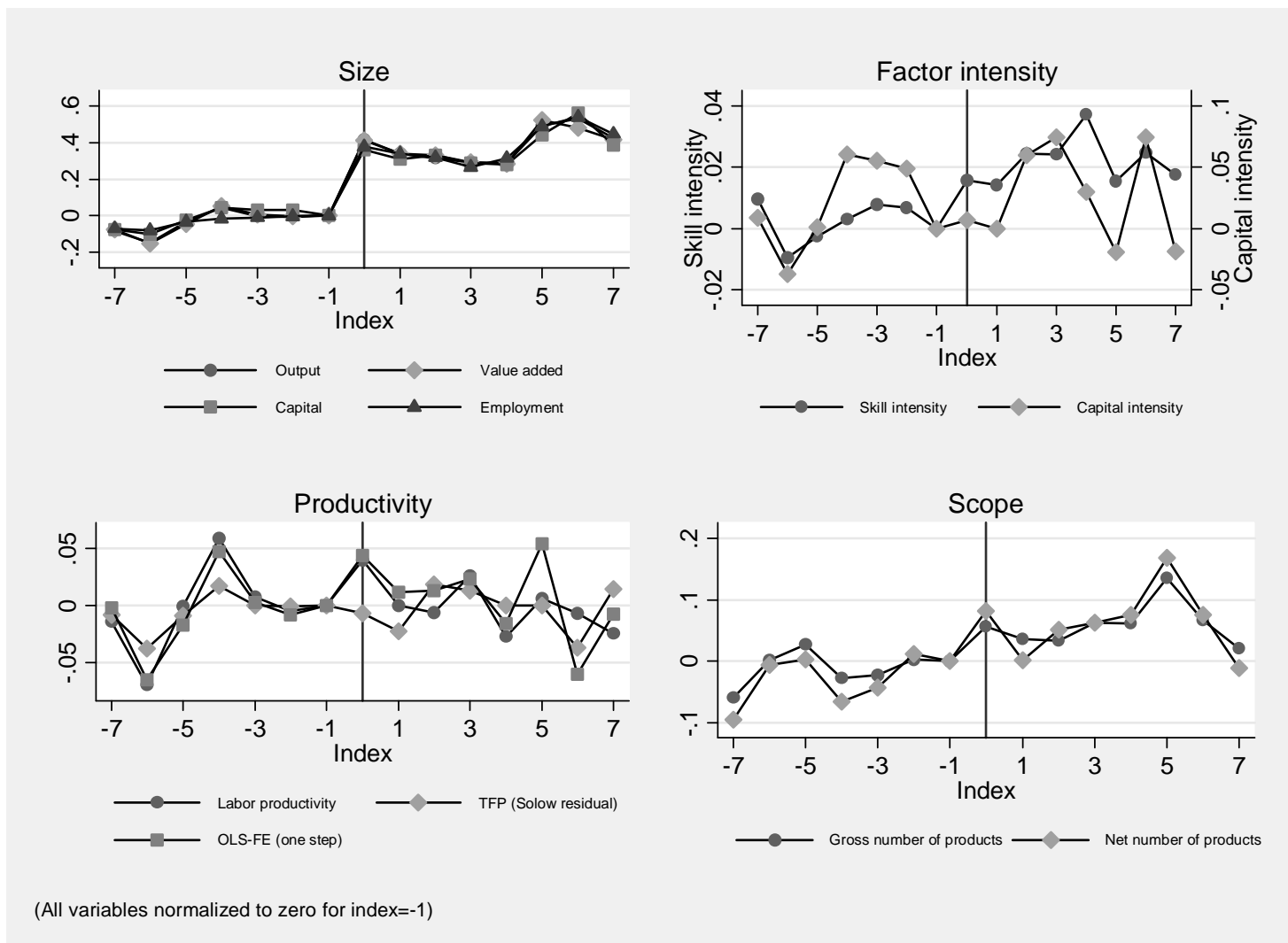
**Notes:** (i) This table reports coefficients on a dummy indicator variable that equals 1 if the firm has applied for any patents up to and including the observation year (conditional on subsequent approval), and 0 otherwise. All dependent variables, except the white- to blue-collar wage ratio, are logged. (ii) The samples are restricted to those firms that enter without a patent and switch to being a patentee later in their life (“switchers”). Additionally, the samples in Column 2 are restricted to the five years before and the five years after the “switch”. (iii) All regressions include firm fixed effects. (iv) Robust standard errors clustered at the 4-digit industry level are in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%. \*\*\* indicates significance at 1%.

**Table 4B: Patenting and Firm Characteristics: Difference-in-differences Effects**

	(1)		(2)	
	Switchers overall		Around the Switch	
<i>Size</i>				
Output	0.45880***	(0.01291)	0.37360***	(0.01226)
Value added	0.45141***	(0.01382)	0.36646***	(0.01332)
Capital stock	0.45525***	(0.01548)	0.37409***	(0.01508)
Employment	0.40201***	(0.01204)	0.33900***	(0.01144)
<i>Factor intensity</i>				
Skill intensity (White- to blue-collar worker ratio)	0.01895***	(0.00218)	0.02187***	(0.00236)
Capital intensity (Capital stock per worker)	0.09346***	(0.01227)	0.08205***	(0.01283)
<i>Productivity</i>				
Labor productivity	0.05679***	(0.00667)	0.03460***	(0.00710)
TFP (Solow residual)	0.02640***	(0.00478)	0.02236***	(0.00506)
OLS-FE (one-step)	0.07006***	(0.00774)	0.04852***	(0.00823)
<i>Scope</i>				
Gross number of products	0.09553***	(0.00676)	0.13320***	(0.00626)
Net number of products	0.01115	(0.00960)	0.04123***	(0.01011)
Number of observations	1,333,963		1,318,009	

**Notes:** (i) This table reports coefficients on a dummy indicator variable that equals 1 if the firm has applied for any patents up to and including the observation year (conditional on subsequent approval), and 0 otherwise. All dependent variables, except the white- to blue-collar wage ratio, are logged. (ii) The samples are restricted to those firms that enter without a patent and switch to being a patentee later in their life (“switchers”), plus the sample of non-patentees (i.e firms that did not apply successfully for a patent any time during the sample period). Additionally, in the samples in Column 2, the data for switching firms are restricted to the five years before and the five years after the “switch”. (iii) All regressions include firm fixed effects as well as 4-digit industry-year effects. (iv) Robust standard errors clustered at the firm level are in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%. \*\*\* indicates significance at 1%.

**Figure 2: Event study analysis: Difference-in-differences relative to nearest neighbor**



**Notes:** i) Points on the graph are coefficients on a dummy indicator variable, which equals 1 if the firm applied (successfully) for a patent, interacted with an index indicating the number of years from patenting. (ii) Specifications include cell-year fixed effects, where each cell consists of exactly one “switcher” (i.e. a firm that switch status from non-patentee to patentee), and one “control” firm which is a non-patentee firm in the same 4 digit industry and same age as the switcher, and nearest in employment size to the “switcher” firm in the closest data year prior to patenting. (iii) The underlying sample consists of approximately 8000 “switchers” and equal number of non-patentee control firms.

**Table 5: Analysis of Scope Results: New Product Sales and Product Counts**

	(1)		(2)		(3)		(4)	
	Coefficient on patent dummy (Table 4A)				Coefficient on patent dummy (Table 4B)			
	Switchers overall		Around the Switch		Switchers overall		Around the Switch	
Total product sales (in 000\$s)	11,002.49***	(403.47)	6,277.51***	(289.90)	5,520.13***	(258.28)	4,427.84***	(179.96)
Old (pre-patenting) product sales (in 000\$s)	400.22*	(205.96)	-1,368.56***	(212.06)	-1,804.04***	(153.61)	-2,170.78***	(139.58)
New (post-patenting) product sales (in 000\$s)	10,602.27***	(358.44)	7,646.07***	(286.69)	7,324.17***	(237.60)	6,598.62***	(171.12)
Gross number of products (count)	5.19***	(0.09)	2.95***	(0.07)	1.04***	(0.062)	0.88***	(0.049)
Net number of products (count)	1.27***	(0.06)	0.86***	(0.06)	0.53***	(0.05)	0.47***	(0.04)
Number of observations	28,823		16,052		57,122		44,351	

**Notes:** (i) This table reports coefficients on a dummy indicator variable that equals 1 if the firm has applied for any patents up to and including the observation year (conditional on subsequent approval), and 0 otherwise. (ii) All variables are winsorized by 2% on both tails of the distribution. (iii) In column 1 and 2, the sample is restricted to those firms that enter without a patent and switch to being patent-owning firm later in their life (“switchers”). In columns 3 and 4, the sample also includes non-patentees (i.e. firms that did not own or apply successfully for a patent any time during the sample period). Additionally, the samples in Column 2 and 4 are restricted (in the case of the sample of switching firms) to the five years before and the five years after the “switch”. (iv) All regressions include firm fixed effects. Columns 3 and 4 also include 4-digit industry-year effects. (v) Robust standard errors clustered at the 4-digit industry level are in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%. \*\*\* indicates significance at 1%.

**Table 6A: Robustness of OLS-FE (One-step) Productivity Estimates**

	(1)	(2)	(3)	(4)	(5)
	Baseline	Alternative capital measure	Split blue and white collar labor	Order 2 translog	Real Sales
Coefficient on patent stock (Table 4)	0.01516*** (0.00413)	0.01923*** (0.00537)	0.01262*** (0.00355)	0.01844*** (0.00351)	0.00834*** (0.00195)
Coefficient on patent dummy (Table 4A, col 1)	0.11319*** (0.01994)	0.11138*** (0.01523)	0.11453*** (0.01133)	0.08543*** (0.01055)	0.06945*** (0.00624)
Coefficient on patent dummy (Table 4B, col 1)	0.07006*** (0.00774)	0.07071*** (0.01157)	0.05494*** (0.00792)	0.10270*** (0.00757)	0.03947*** (0.00448)

**Notes:** (i) This table reports coefficients on depreciated patent stock or on patent dummy variables. (ii) The sample in row 1 is all patentees (recall that patent stock is undefined for non-patentees). The sample in row 2 is restricted to those firms that enter without a patent and switch to being a patentee later in their life (“switchers”). Row 3 includes the sample of switchers in row 2 plus the sample of non-patentees (i.e. firms that did not own or apply successfully for a patent any time during the sample period). (iii) All regressions include firm fixed effects. Regressions in rows 1 and 3 also include 4-digit industry-year effects (iv) Robust standard errors clustered at 4-digit industry level (firm level in row 2) are in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%. \*\*\* indicates significance at 1%.

**Table 6B: GMM Analysis of Productivity**

	(1)	(2)	(3)	(4)	(5)
	Baseline OLS-FE	Difference GMM (Lag 2)	Difference GMM (Lags 2, 3)	System GMM (Lag 2)	System GMM (Lags 2, 3)
Capital	0.16769*** (0.00934)	2.08765** (1.00861)	0.81726*** (0.13406)	0.57061*** (0.01778)	0.57060*** (0.01771)
Employment	0.77485*** (0.01173)	1.25678** (0.54302)	0.57624*** (0.09359)	0.31613*** (0.02905)	0.31477*** (0.02892)
Patent stock	0.01516*** (0.00413)	1.06969 (0.70884)	0.19208* (0.09894)	0.07324*** (0.00710)	0.07396*** (0.00705)
Number of observations	66,423	66,423	66,423	66,423	66,423
Hansen p-value	NA	NA	0.0003	0.0000	0.0000
m2 p-value	NA	0.187	0.937	0.689	0.685

Notes: (i) The first column reports OLS fixed effects estimates (corresponding to results in Table 4) for comparison; it includes firm fixed effects and 4-digit industry-year effects. (ii) Columns 2 to 5 include year dummies (unreported). (iii) In “difference” GMM (columns 2 and 3), first differences of capital, labor and patent stock are instrumented using suitable lags of the same variables in levels. In column 2, a single lag of order 2 is used; in column 3 lags of order 2 and order 3 are used. (iv) System GMM extends the set of moment conditions used in difference GMM. In particular, equations in levels are also estimated, using suitably lagged first differences as instruments. In column 4, first differences are instrumented with order 2 lag of the levels and levels are instrumented with order 2 lag of the first differences. In column 5, first differences are instrumented with order 2 and order 3 lags of the levels and levels are instrumented with order 2 and order 3 lags of the first differences. (vi) m2 is a test for second order serial correlation proposed by Arellano and Bond (1991). (vii) In columns 2-5, a two-step GMM estimator is used. Robust, Windmeijer (2005) corrected standard errors are reported in parentheses. In column 1, standard errors are clustered at 4-digit industry level; \* indicates significance at 10%, \*\* indicates significance at 5%. \*\*\* indicates significance at 1%.

**Table 7A: GMM Analysis of Size Effects**

Dependent variable	DIFFERENCE	DIFFERENCE	SYSTEM GMM	SYSTEM GMM
	GMM (LAG 2)	GMM (LAGS 2, 3)	(LAG 2)	(LAGS 2, 3)
Output	0.86647** (0.35944)	0.86639** (0.36372)	0.38920*** (0.01331)	0.38905*** (0.01331)
Hansen p-value	NA	0.4670	0.0876	0.1410
m2 p-value	0.0000	0.0000	0.0000	0.0000
Value added	0.81222** (0.36132)	0.81232** (0.36215)	0.38722*** (0.01316)	0.38721*** (0.01316)
Hansen p-value	NA	0.8780	0.1510	0.3480
m2 p-value	0.0001	0.0001	0.0000	0.0000
Capital stock	0.85276** (0.39936)	0.83972** (0.40587)	0.36185*** (0.01505)	0.36195*** (0.01505)
Hansen p-value	NA	0.2920	0.1250	0.1310
m2 p-value	0.0000	0.0000	0.0000	0.0000
Employment	-1.62139** (0.69445)	-1.54659** (0.69557)	0.32487*** (0.01168)	0.32436*** (0.01167)
Hansen p-value	NA	0.4920	0.0000	0.0000
m2 p-value	0.0077	0.0099	0.1060	0.1060
Number of observations	66,423	66,423	66,423	66,423

**Notes:** (i) This table reports coefficients on log depreciated patent stock. All dependent variables are logged. (ii) Lagged levels are used as instruments in first differenced equations and lagged differences are used as instruments for equations in levels. System GMM uses equations in both levels and differences as proposed by Blundell and Bond (1998). (iii) m2 is a test for second order serial correlation proposed by Arellano and Bond (1991). (iv) Two-step, Windmeijer (2005) corrected standard errors are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%. \*\*\* indicates significance at 1%.

**Table 7B: Link between Patent Quality and Size Effects**

Dependent variable	Output		Value Added		Capital Intensity		Employment	
Patent ownership dummy	0.33467 [0.0429]***	0.43929 [0.0343]* **	0.31909 [0.0474]* **	0.43018 [0.0378]* **	0.52744 [0.0507]* **	0.623 [0.0380]* **	0.2751 [0.0392]* **	0.35815 [0.0298]* **
Log number of forward citations to first-year patents * Patent Dummy	0.12553 [0.0232]* **		0.13661 [0.0254] ***		0.10469 [0.0256]* **		0.10167 [0.0213]* **	
Mean number of citations per patent for first-year patents * Patent Dummy		0.0193 [0.0050] ***		0.02146 [0.0055]* **		0.01471 [0.0048] ***		0.01591 [0.0042]* **
Number of observations	18,215	18,215	18,215	18,215	18,215	18,215	18,215	18,215

**Notes:** i) Patent ownership dummy is an indicator variable that equals 1 if the firm has applied for any patents up to and including the observation year. (ii) The dependent variables are all logged. (iii) The samples are restricted to those firms that enter without a patent and switch to being a patentee later in their life (“switchers”). (iv) The number of citations for any given patent is computed as the number of patents that cite the focal patent, and were granted between (and including) the application year of the focal patent and 1999. (v) Robust standard errors clustered at the 4-digit industry level are in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%. \*\*\* indicates significance at 1%.

## **Supplementary appendix of results for**

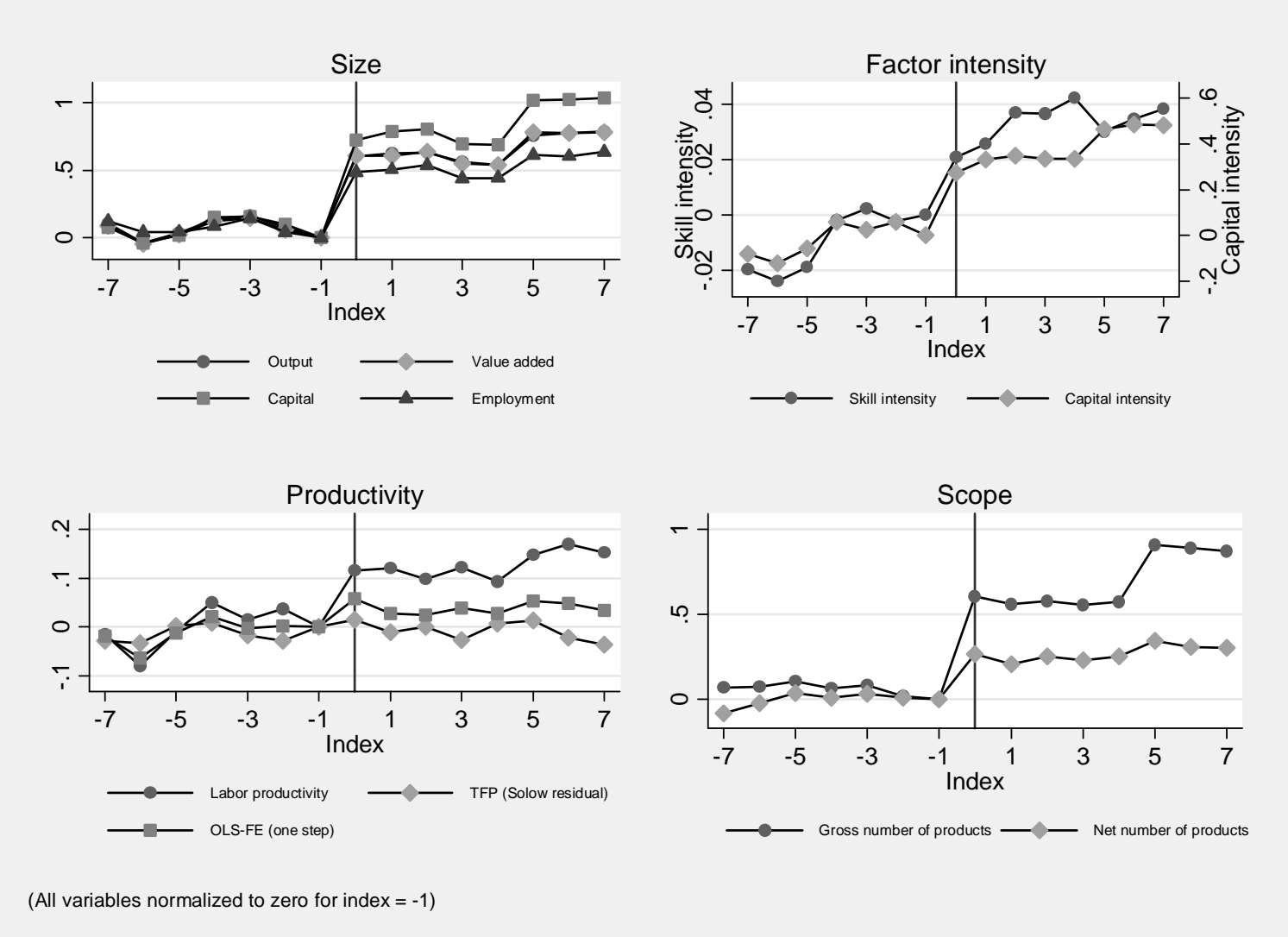
“What happens when firms patent? New evidence from US economic census data”, by Natarajan Balasubramanian<sup>1</sup> and Jagadeesh Sivadasan<sup>2</sup>, 2009

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<sup>1</sup> balasubn@fiu.edu, Florida International University

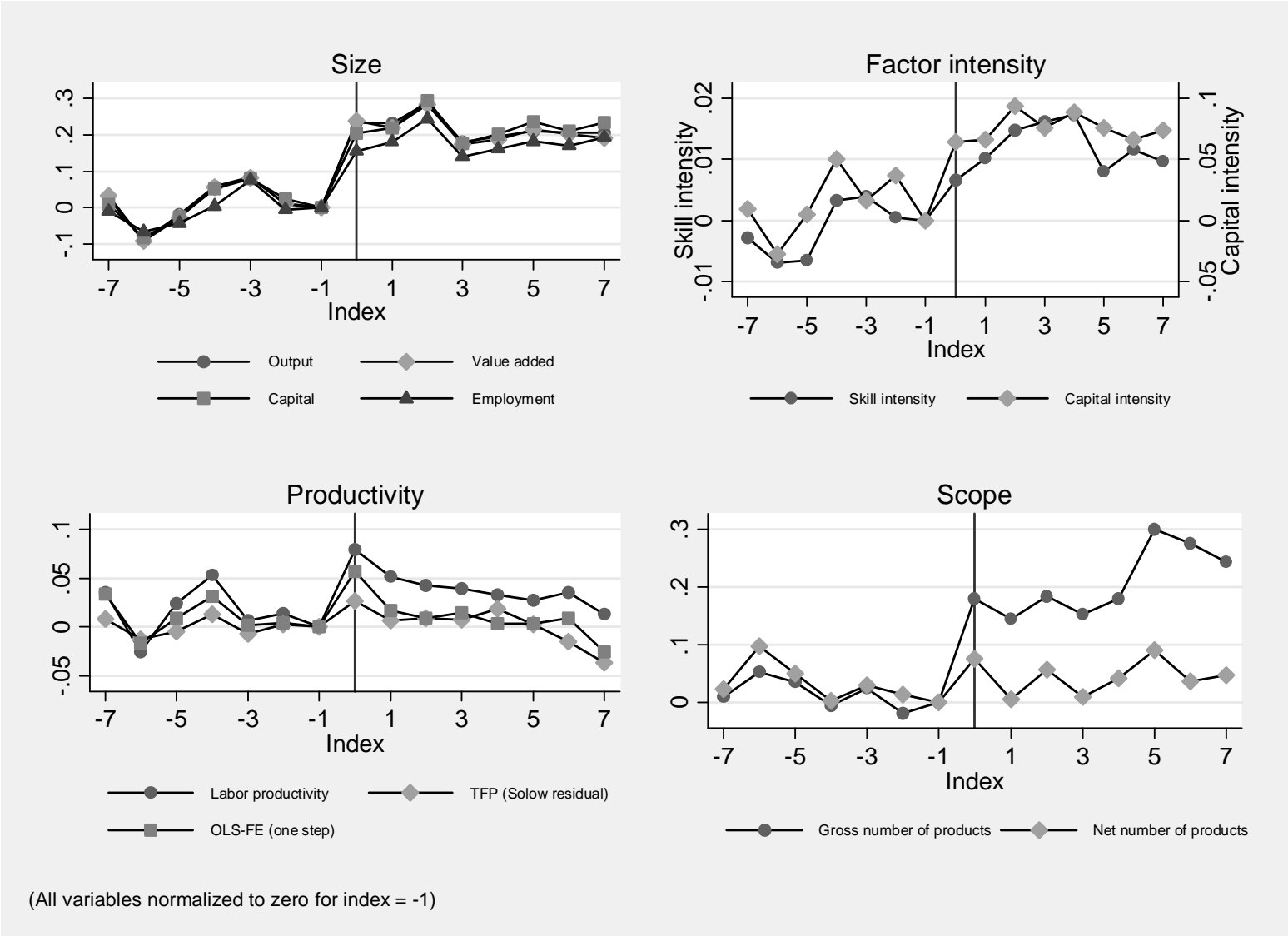
<sup>2</sup> jagadees@umich.edu, University of Michigan

Figure A.1: Event study analysis: Before-after effects



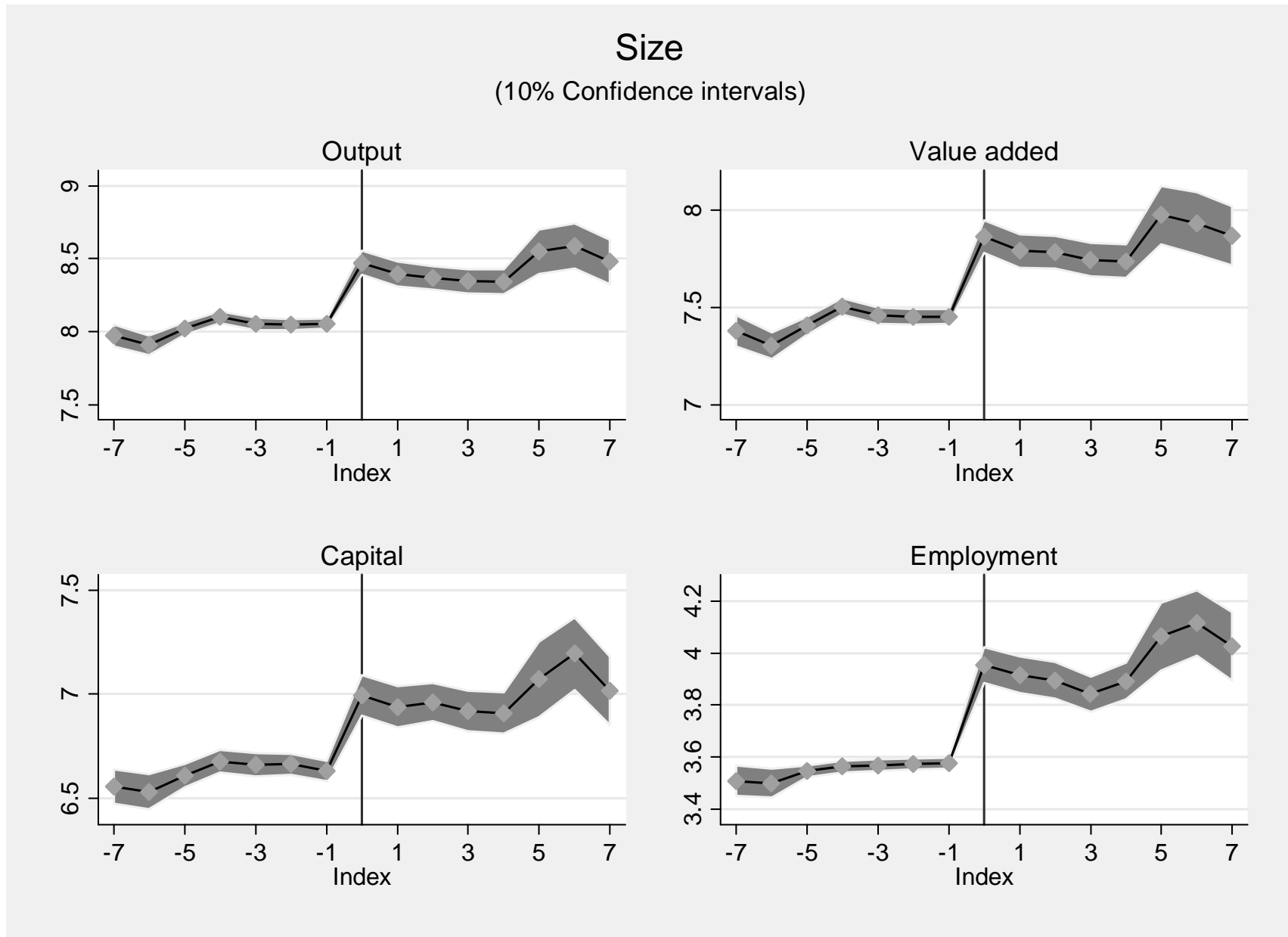
**Notes:** i) Points on the graph are coefficients on a dummy indicator variable, which equals 1 if the firm applied (successfully) for a patent, interacted with an index indicating the number of years from patenting. All dependent variables, except the white- to blue-collar wage ratio, are logged. (ii) Specifications include no fixed effects, so that dummy coefficient reflects the mean for each index. (iii) The underlying sample consists only of “switchers” i.e. firms that switch status from non-patentee to patentee. The number of observations in each of the underlying regressions is 18,572.

Figure A.2: Event Study Analysis (Industry-year-age effects)



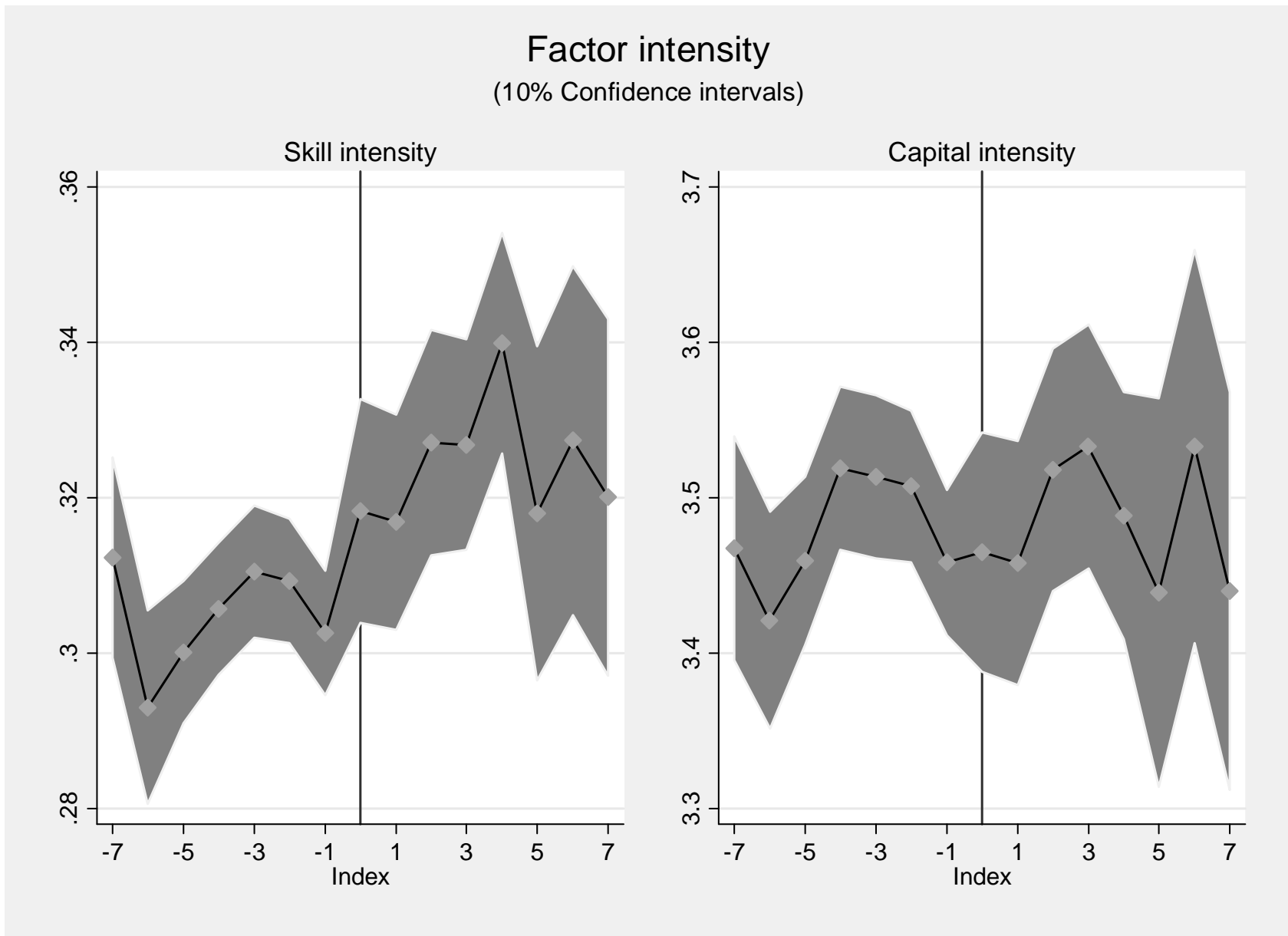
**Notes:** i) Points on the graph are coefficients on a dummy indicator variable, which equals 1 if the firm applied (successfully) for a patent, interacted with an index indicating the number of years from patenting. All dependent variables, except the white- to blue-collar wage ratio, are logged. (ii) All specifications include 4-digit industry-year-age quintile fixed effects. (iii) The underlying sample consists of “switchers” i.e. firms that switch status from non-patentee to patentee, and non-patentees. The number of observations in each of the underlying regressions is 18,572. (iv) All variables are normalized to zero for index=-1.

Figure A.3a: Size variables (with nearest neighbor cell-year effects)



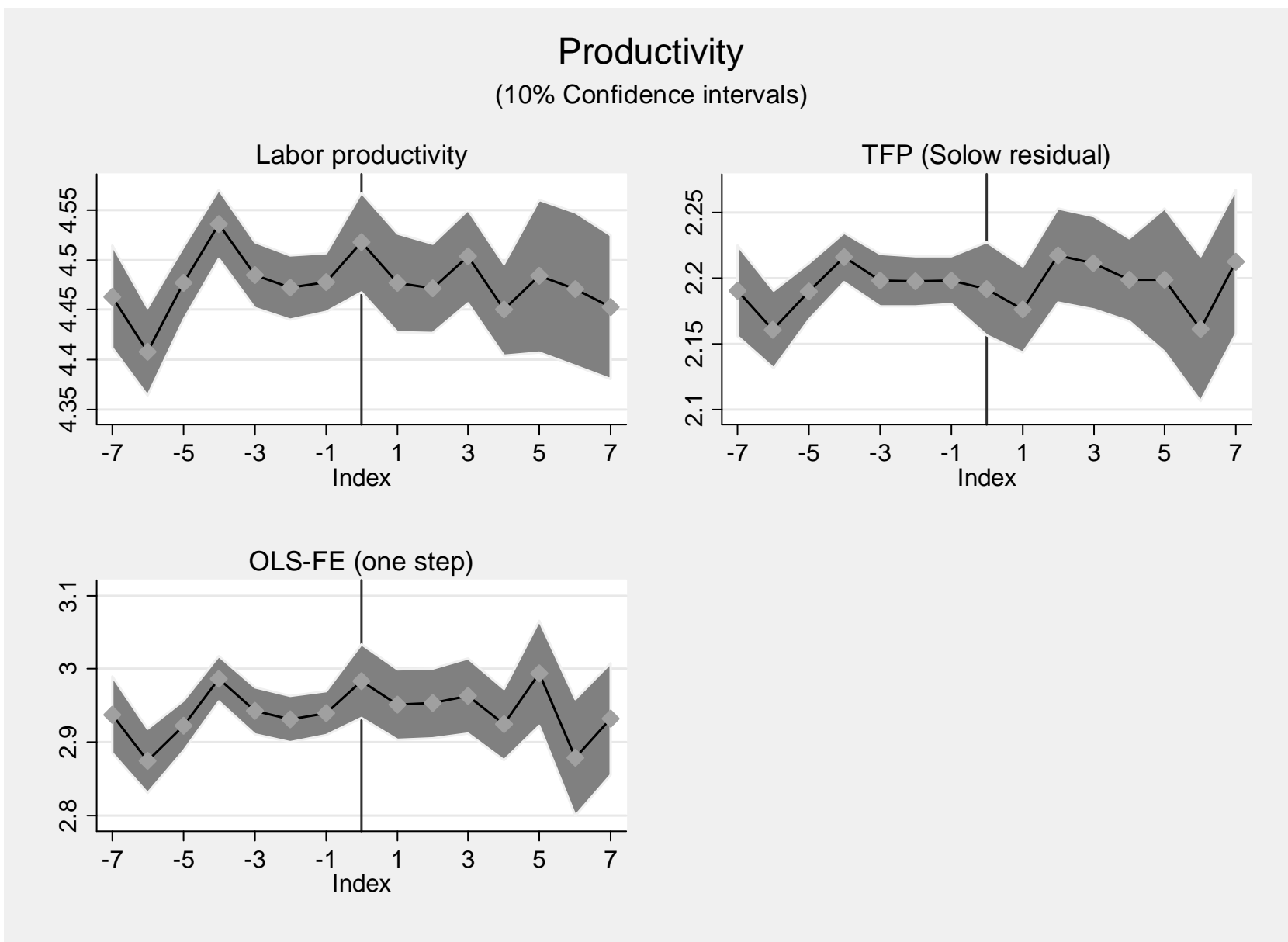
Notes: See notes to Figure 2 in text

Figure A.3b: Factor intensity variables (with nearest neighbor cell-year effects)



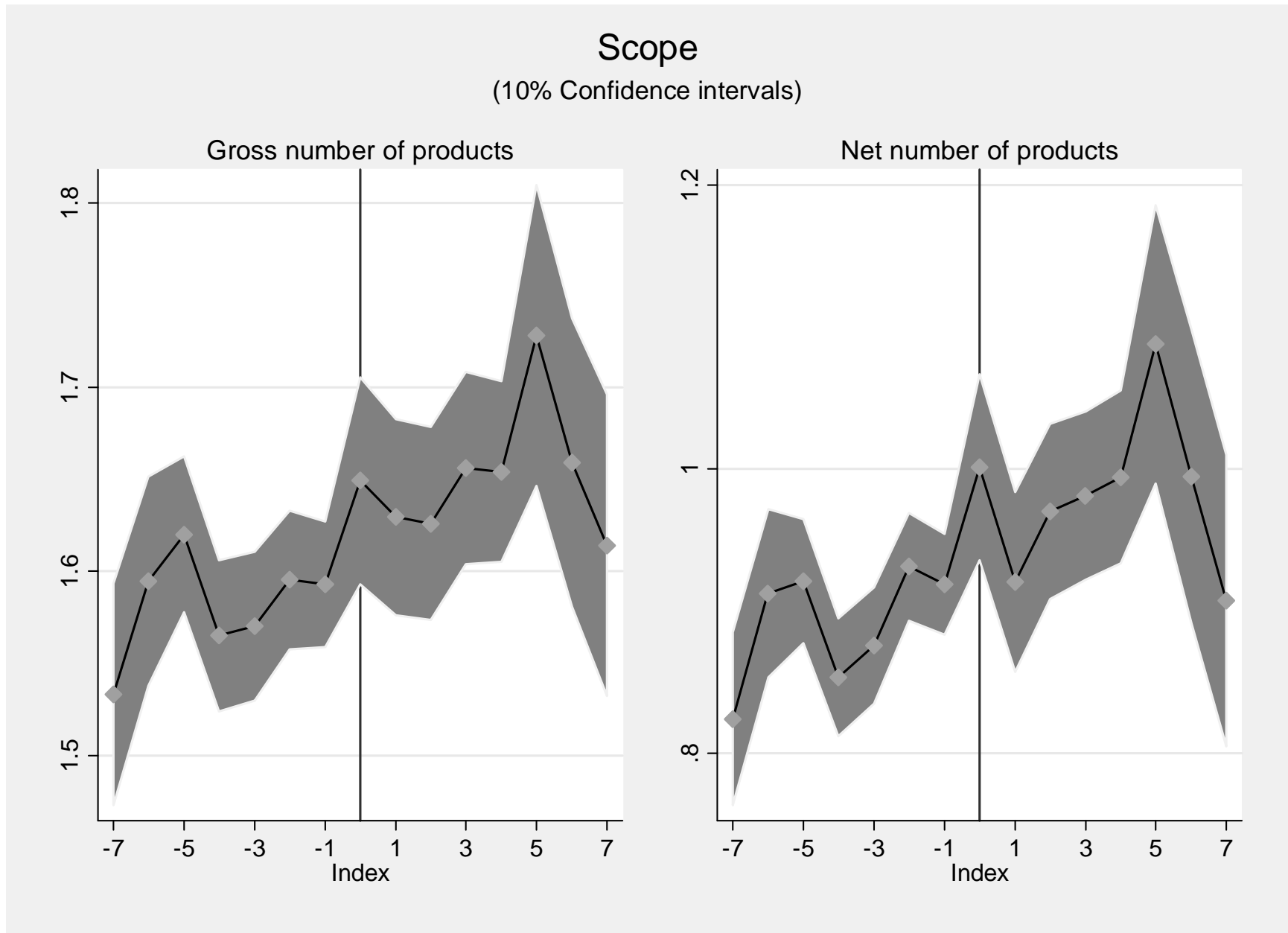
Notes: See notes to Figure 2 in text

Figure A.3c: Productivity variables (with nearest neighbor cell-year effects)



Notes: See notes to Figure 2 in text

Figure A.3d: Scope variables (with nearest neighbor cell-year effects)



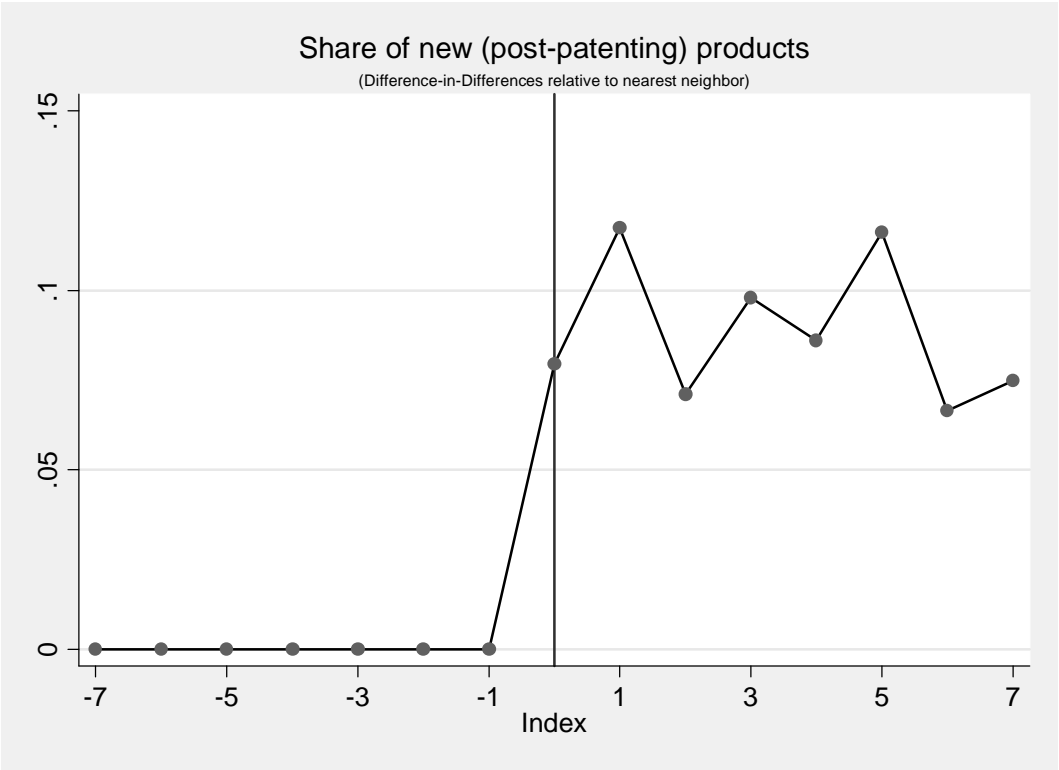
Notes: See notes to Figure 2 in text

Table A.1: Scope results: Robustness to other controls

	Elasticity to patent stock (Table 3)		Coefficient on patent dummy (Table 4A)		Coefficient on patent dummy (Table 4B)	
			Switchers overall		Switchers overall	
<b>Gross Number of Products</b>						
(i) Unconditional	0.04366***	(0.00588)	0.78727***	(0.00753)	0.09553***	(0.00676)
<i>Including additional controls for</i>						
(ii) Output	0.01731***	(0.00262)	0.60074***	(0.00826)	0.03912***	(0.00650)
(iii) Output, skill and capital intensity	0.01774***	(0.00261)	0.57669***	(0.00859)	0.03911***	(0.00648)
(iv) Employment	0.01665***	(0.00259)	0.63483***	(0.00801)	0.04090***	(0.00644)
(v) Employment, skill and capital intensity	0.01655***	(0.00260)	0.57910***	(0.00876)	0.03951***	(0.00645)
(iv) Capital	0.02442***	(0.00268)	0.60380***	(0.00919)	0.06575***	(0.00664)
(v) Capital, skill and capital intensity	0.01691***	(0.00260)	0.58141***	(0.00879)	0.04314***	(0.00646)
<b>Net Number of Products</b>						
(i) Unconditional	0.03561***	(0.00354)	0.33172***	(0.01008)	0.01115	(0.00960)
<i>Including additional controls for</i>						
(ii) Output	0.00475	(0.00465)	0.20318***	(0.01112)	-0.03746***	(0.00945)
(iii) Output, skill and capital intensity	0.00563	(0.00464)	0.20814***	(0.01147)	-0.03761***	(0.00943)
(iv) Employment	0.00317	(0.00456)	0.21551***	(0.01080)	-0.03541***	(0.00943)
(v) Employment, skill and capital intensity	0.00266	(0.00458)	0.20561***	(0.01149)	-0.03417***	(0.00943)
(iv) Capital	0.01887***	(0.00481)	0.22770***	(0.01184)	-0.00974	(0.00956)
(v) Capital, skill and capital intensity	0.00294	(0.00458)	0.20775***	(0.01150)	-0.03074***	(0.00944)

Notes: See notes to Table 3, Table 4A and Table 4B in the text. Standard errors clustered at 4-digit industry level (for 4A and Table 3) and firm level (for Table 4B) are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.

Figure A.4: Event study analysis: share of new products -- Difference-in-differences relative to nearest neighbor



**Notes:** i) Points on the graph are coefficients on a dummy indicator variable, which equals 1 if the firm applied (successfully) for a patent, interacted with an index indicating the number of years from patenting. (ii) Specifications include cell-year fixed effects, where each cell consists of exactly one “switcher” (i.e. a firm that switches status from non-patentee to patentee), and one “control” firm which is a non-patentee firm in the same 4-digit industry and same age as the switcher, and nearest in employment size to the “switcher” firm in the closest data year prior to patenting. (iii) The underlying sample consists of approximately 8,000 “switchers” and an equal number of non-patentee control firms.

Table A.2: Margins and patenting

Dependent variable:	Markup (Net profits/sales)			Markup (Net profits/value added)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Elasticity estimate (Table 3)	Before-after effect (Table 4A)	Difference-in-Differences effect (Table 4B)	Elasticity estimate (Table 3)	Before-after effect (Table 4A)	Difference-in-Differences effect (Table 4B)
Coefficient on patent stock	-0.00152* (0.00082)			0.00145*** (0.00029)		
Number of observations	60,708			60,708		
Coefficient on patent dummy		0.02266*** (0.00225)	0.00272 (0.00202)		0.02723*** (0.00116)	0.00494*** (0.00111)
Number of observations		31,336	1,333,963		31,336	1,333,963

Notes: Refer notes to tables 3, 4A and 4B in the text. All specifications include firm fixed effects. Table 3 and Table 4B estimates also include 4-digit industry year effects. Net profits are defined as sales less the sum of materials costs, labor costs and financial costs (calculated as 8.5% of assets, following Aghion et al (2005)). Standard errors clustered at 4-digit industry level for Tables 4 and 4A and at firm level for Table 4B are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.

Table A.3: GMM analysis -- All variables

	<b>DIFFERENCE GMM (LAG 2)</b>	<b>DIFFERENCE GMM (LAGS 2, 3)</b>	<b>SYSTEM GMM (LAG 2)</b>	<b>SYSTEM GMM (LAGS 2, 3)</b>
<i>Size</i>				
Output	0.86647** (0.35944)	0.86639** (0.36372)	0.38920*** (0.01331)	0.38905*** (0.01331)
Hansen p-value	NA	0.4670	0.0876	0.1410
m2 p-value	0.0000	0.0000	0.0000	0.0000
Value added	0.81222** (0.36132)	0.81232** (0.36215)	0.38722*** (0.01316)	0.38721*** (0.01316)
Hansen p-value	NA	0.8780	0.1510	0.3480
m2 p-value	0.0001	0.0001	0.0000	0.0000
Capital stock	0.85276** (0.39936)	0.83972** (0.40587)	0.36185*** (0.01505)	0.36195*** (0.01505)
Hansen p-value	NA	0.2920	0.1250	0.1310
m2 p-value	0.0000	0.0000	0.0000	0.0000
Employment	-1.62139** (0.69445)	-1.54659** (0.69557)	0.32487*** (0.01168)	0.32436*** (0.01167)
Hansen p-value	NA	0.4920	0.0000	0.0000
m2 p-value	0.0077	0.0099	0.1060	0.1060
<i>Factor intensity</i>				
Skill intensity	0.01906 (0.03780)	0.01537 (0.03778)	0.00923*** (0.00111)	0.00922*** (0.00111)
Hansen p-value	NA	0.3800	0.7910	0.6610
m2 p-value	0.0153	0.0109	0.0009	0.0009
Capital intensity	2.58166*** (0.97172)	2.42168** (0.98295)	0.04605*** (0.00688)	0.04581*** (0.00689)
Hansen p-value	NA	0.2870	0.0000	0.0000
m2 p-value	0.0005	0.0010	0.0000	0.0000

Table A.3: GMM analysis (...ctd)

	DIFFERENCE GMM (LAG 2)	DIFFERENCE GMM (LAGS 2, 3)	SYSTEM GMM (LAG 2)	SYSTEM GMM (LAGS 2, 3)
<i>Productivity</i>				
Labor productivity	2.48786*** (0.90240)	2.38693*** (0.91063)	0.05173*** (0.00416)	0.05169*** (0.00416)
Hansen p-value	NA	0.4100	0.0000	0.0000
m2 p-value	0.0009	0.0014	0.0000	0.0000
TFP (Solow residual)	-0.23638 (0.14984)	-0.0673 (0.16002)	0.01931*** (0.00329)	0.02003*** (0.00329)
Hansen p-value	NA	0.0000	0.0296	0.0000
m2 p-value	0.1360	0.4510	0.0808	0.0801
GMM (1-step)	1.06969 (0.70884)	0.19208* (0.09894)	0.07324*** (0.00710)	0.07396*** (0.00705)
Hansen p-value	NA	0.0003	0.0000	0.0000
m2 p-value	0.1870	0.9370	0.6890	0.6850
<i>Scope</i>				
Gross number of products	1.18713*** (0.44143)	1.13419** (0.44683)	-0.02327** (0.01028)	-0.02404** (0.01028)
Hansen p-value	NA	0.3470	0.0000	0.0000
m2 p-value	0.0000	0.0000	0.0000	0.0000
Net number of products	-2.88279*** (1.10424)	-2.82195*** (1.09542)	0.10410*** (0.00866)	0.10413*** (0.00866)
Hansen p-value	NA	0.7490	0.0000	0.0000
m2 p-value	0.0163	0.0163	0.0054	0.0054

**Notes:** (i) This table reports coefficients on log depreciated patent stock. All dependent variables, except the white- to blue-collar wage ratio, are logged. (ii) Lagged levels are used as instruments in first differenced equations and lagged differences are used as instruments for equations in levels. System GMM uses equations in both levels and differences as proposed by Blundell and Bond (1998). (iii) m2 is a test for second order serial correlation proposed by Arellano and Bond (1991). (iv) Two-step, Windmeijer-corrected standard errors are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.

Table A.4: Interactions with patent quality – All variables

Dependent variable	Dummy	Dummy * Q1	Dummy	Dummy * Q2
<i>Size</i>				
Output	0.33467 [0.04292]**	0.12553 [0.02325]**	0.43929 [0.03432]**	0.0193 [0.00501]**
Value added	0.31909 [0.04737]**	0.13661 [0.02538]**	0.43018 [0.03785]**	0.02146 [0.00549]**
Capital stock	0.52744 [0.05073]**	0.10469 [0.02561]**	0.623 [0.03797]**	0.01471 [0.00480]**
Employment	0.2751 [0.03919]**	0.10167 [0.02126]**	0.35815 [0.02982]**	0.01591 [0.00423]**
<i>Factor intensity</i>				
Skill intensity	0.02526 [0.00798]**	0.01027 [0.00398]**	0.03345 [0.00562]**	0.00164 [0.00066]*
Capital intensity	0.29574 [0.04345]**	0.02592 [0.02061]	0.326 [0.03059]**	0.00255 [0.00327]
<i>Productivity</i>				
Labor productivity	0.05957 [0.02400]*	0.02386 [0.01194]*	0.08114 [0.01776]**	0.00339 [0.00214]
TFP (Solow residual)	-0.04114 [0.02057]*	0.02912 [0.00974]**	-0.01933 [0.01452]	0.00489 [0.00168]**
OLS-FE (one-step)	-0.00223 [0.02973]	0.03751 [0.01442]**	0.02556 [0.02260]	0.00632 [0.00261]*
<i>Scope</i>				
Gross number of products	0.45888 [0.02094]**	0.0413 [0.01036]**	0.50029 [0.01573]**	0.00519 [0.00192]**
Net number of products	0.18468 [0.03321]**	0.0308 [0.01602]+	0.22035 [0.02318]**	0.00307 [0.00242]
Number of observations		18,215		18,215

Notes: See notes to Table 8 in the text. Q1 is the log total number of forward citations to the patents in the first year of patenting; and Q2 is number of citations per patent for patents in the first year of patenting. Standard errors clustered at 4-digit industry level are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.

Table A.5: Robustness to detailed demand effects

Dependent variable: Log Output	All Patentees	Switchers (overall)	Around the Switch
Coefficient on patent stock (as in Table 3, 5-digit industry code-year fixed effects)	0.05776*** (0.0064)		
Number of observations	310,164		
Coefficient on patent stock (as in Table 3, specialized firms, 4-digit industry-year effects)	0.15159*** (0.00740)		
Number of observations	49,973		
Coefficient on patent dummy (as in Table 4B, specialized firms, 4-digit industry-year effects)		0.49126*** (0.01406)	0.39391*** (0.01334)
Number of observations		1,333,963	1,318,009
Coefficient on patent dummy (as in Table 4B, SMSA-2 digit industry code-year fixed effects)		0.60037*** (0.01815)	0.48684*** (0.01736)
Number of observations		823,549	814,497

Notes: See notes to Table 3 and Table 4B in the text. All regressions include firm fixed effects. Specialized firms are defined as firms for which the share of total output of the predominant 5-digit sector is at least 80%. Standard errors clustered at 4-digit industry level are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.

Table A.6: Patenting and firm characteristics: Sample of specialized firms

	Elasticity to patent stock (Table 3)		Coefficient on patent dummy (Table 4A)				Coefficient on patent dummy (Table 4B)			
			Switchers overall		Around the Switch		Switchers overall		Around the Switch	
<i>Size</i>										
Output	0.15159***	(0.00740)	0.80730***	(0.01636)	0.56590***	(0.01944)	0.49126***	(0.01406)	0.39391***	(0.01334)
Value added	0.14356***	(0.00803)	0.81934***	(0.01760)	0.57283***	(0.02120)	0.48688***	(0.01503)	0.38925***	(0.01445)
Capital stock	0.16721***	(0.00940)	1.06507***	(0.01881)	0.72532***	(0.02360)	0.47867***	(0.01684)	0.39218***	(0.01637)
Employment	0.13712***	(0.00679)	0.61683***	(0.01459)	0.46606***	(0.01753)	0.43781***	(0.01306)	0.36205***	(0.01236)
<i>Factor intensity</i>										
Skill intensity	0.00537***	(0.00136)	0.05599***	(0.00258)	0.04278***	(0.00365)	0.02423***	(0.00241)	0.02631***	(0.00258)
Capital intensity	0.03905***	(0.00768)	0.55469***	(0.01520)	0.34449***	(0.02018)	0.09121***	(0.01354)	0.08577***	(0.01406)
<i>Productivity</i>										
Labor productivity	0.01447***	(0.00386)	0.19047***	(0.00838)	0.09985***	(0.01141)	0.05345***	(0.00735)	0.03186***	(0.00779)
TFP (Solow residual)	0.00102	(0.00293)	-0.00073	(0.00681)	0.00381	(0.00894)	0.03271***	(0.00516)	0.02560***	(0.00541)
OLS-FE (one-step)	0.00987**	(0.00478)	0.11072***	(0.01199)	0.07324***	(0.01597)	0.07690***	(0.00847)	0.05193***	(0.00891)
<i>Scope</i>										
Gross number of products	0.02739***	(0.00360)	0.78913***	(0.00805)	0.51271***	(0.00950)	0.09872***	(0.00719)	0.13299***	(0.00659)
Net number of products	0.00712	(0.00591)	0.33545***	(0.01045)	0.21231***	(0.01504)	0.0094	(0.01000)	0.03246***	(0.01059)
Number of observations	49,973		27,275		13,558		1,311,830		1,298,113	

Notes: The sample includes only specialized firms. Specialized firms are defined as firms for which the share of total output of the predominant 5-digit sector is at least 80%. See also notes to Table 3, Table 4A and Table 4B in the text. Standard errors clustered at 4-digit industry level (for 4A and Table 3) and firm level (for Table 4B) are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.

Table A.7: Patenting and firm characteristics: Robustness to excluding potential acquirers

	Coefficient on patent dummy (Table 4A)				Coefficient on patent dummy (Table 4B)			
	Switchers overall		Around the Switch		Switchers overall		Around the Switch	
<i>Size</i>								
Output	0.80575***	(0.01671)	0.57359***	(0.02027)	0.49102***	(0.01430)	0.40239***	(0.01379)
Value added	0.81813***	(0.01796)	0.58219***	(0.02201)	0.48812***	(0.01527)	0.40149***	(0.01487)
Capital stock	1.06054***	(0.01919)	0.72837***	(0.02453)	0.47217***	(0.01706)	0.39395***	(0.01684)
Employment	0.61173***	(0.01500)	0.47271***	(0.01835)	0.43605***	(0.01332)	0.37035***	(0.01282)
<i>Factor intensity</i>								
Skill intensity (white- to blue-collar worker ratio)	0.05715***	(0.00263)	0.04428***	(0.00380)	0.02504***	(0.00243)	0.02768***	(0.00266)
Capital intensity (Capital stock per worker)	0.55690***	(0.01540)	0.34425***	(0.02088)	0.08779***	(0.01361)	0.08257***	(0.01441)
<i>Productivity</i>								
Labor productivity	0.19402***	(0.00851)	0.10087***	(0.01185)	0.05497***	(0.00741)	0.03204***	(0.00800)
TFP (Solow residual)	0.00073	(0.00698)	0.00638	(0.00934)	0.03415***	(0.00525)	0.02911***	(0.00559)
OLS-FE (one-step)	0.11411***	(0.01159)	0.07843***	(0.01635)	0.08128***	(0.00851)	0.05876***	(0.00909)
<i>Scope</i>								
Gross number of products	0.78529***	(0.00812)	0.51182***	(0.00982)	0.09136***	(0.00723)	0.13166***	(0.00673)
Net number of products	0.32314***	(0.01074)	0.20239***	(0.01563)	-0.00144	(0.01015)	0.02470**	(0.01084)
Number of observations	27,175		13,104		1,329,802		1,315,731	

Notes: The sample excludes firms that appear to acquire another firm in the five-year period prior to and including the year that it switches status from non-patentee to patentee. See also notes to Table 4A and Table 4B in the text. Standard errors clustered at 4-digit industry level (for 4A) and firm level (for Table 4B) are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.

Table A.8: Patenting and firm characteristics: Robustness to excluding multi-unit firms

	Coefficient on patent dummy (Table 4A)				Coefficient on patent dummy (Table 4B)			
	Switchers overall		Around the Switch		Switchers overall		Around the Switch	
<i>Size</i>								
Output	0.86481***	(0.01749)	0.61283***	(0.02108)	0.53756***	(0.01520)	0.43504***	(0.01452)
Value added	0.88087***	(0.01872)	0.62448***	(0.02284)	0.53849***	(0.01617)	0.43562***	(0.01563)
Capital stock	1.10631***	(0.02015)	0.75419***	(0.02561)	0.50632***	(0.01823)	0.41517***	(0.01772)
Employment	0.67538***	(0.01566)	0.51576***	(0.01913)	0.48649***	(0.01417)	0.40513***	(0.01349)
<i>Factor intensity</i>								
Skill intensity (white- to blue-collar worker ratio)	0.06051***	(0.00278)	0.04603***	(0.00399)	0.02751***	(0.00261)	0.02876***	(0.00283)
Capital intensity (Capital stock per worker)	0.54589***	(0.01633)	0.33063***	(0.02180)	0.07674***	(0.01462)	0.07140***	(0.01515)
<i>Productivity</i>								
Labor productivity	0.18943***	(0.00890)	0.09707***	(0.01228)	0.05107***	(0.00788)	0.02990***	(0.00839)
TFP (Solow residual)	0.00614	(0.00729)	0.01095	(0.00970)	0.03934***	(0.00555)	0.03189***	(0.00584)
OLS-FE (one-step)	0.11540***	(0.01211)	0.08139***	(0.01711)	0.09029***	(0.00893)	0.06508***	(0.00947)
<i>Scope</i>								
Gross number of products	0.80448***	(0.00861)	0.52100***	(0.01030)	0.10420***	(0.00774)	0.13874***	(0.00710)
Net number of products	0.35491***	(0.01094)	0.22813***	(0.01609)	0.01548	(0.01057)	0.04154***	(0.01124)
Number of observations	23,510		11,810		1,257,565		1,245,865	

Notes: The sample excludes multi-unit firms. See also notes to Table 4A and Table 4B in the text. Standard errors clustered at 4-digit industry level (for 4A) and firm level (for Table 4B) are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.

Table A.9: Patenting and firm characteristics: Public (listed) firms only

	Elasticity to patent stock (Table 3)		Coefficient on patent dummy (Table 4A)				Coefficient on patent dummy (Table 4B)			
			Switchers overall		Around the Switch		Switchers overall		Around the Switch	
<i>Size</i>										
Output	0.19749***	(0.02272)	0.54771***	(0.11132)	0.43044***	(0.13675)	0.30573*	(0.17282)	0.18691	(0.21028)
Value added	0.19145***	(0.02403)	0.55316***	(0.13016)	0.45754***	(0.16470)	0.30594	(0.18673)	0.11365	(0.23296)
Capital stock	0.20132***	(0.02541)	0.69401***	(0.11229)	0.53791***	(0.14550)	0.39399**	(0.19948)	0.32101	(0.22713)
Employment	0.18379***	(0.02011)	0.27764***	(0.09448)	0.24786*	(0.12722)	0.29919**	(0.14487)	0.2517	(0.17896)
<i>Factor intensity</i>										
Skill intensity	-0.00248	(0.00358)	0.01806	(0.01773)	0.02006	(0.02789)	-0.01045	(0.03088)	0.03154	(0.04536)
Capital intensity	0.00881	(0.01672)	0.47080***	(0.08814)	0.36143***	(0.13343)	0.06839	(0.17108)	0.14044	(0.21519)
<i>Productivity</i>										
Labor productivity	0.0137	(0.01102)	0.27007***	(0.06073)	0.18257**	(0.08625)	0.00655	(0.09185)	-0.06479	(0.10764)
TFP (Solow residual)	0.00438	(0.00864)	-0.03860	(0.04249)	0.00632	(0.06391)	-0.00278	(0.06021)	-0.06014	(0.08293)
OLS-FE (one-step)	0.02041	(0.01438)	0.20144**	(0.08882)	0.16014	(0.11788)	0.00853	(0.10979)	-0.12278	(0.14999)
<i>Scope</i>										
Gross number of products	0.04971***	(0.00866)	0.64904***	(0.05601)	0.52368***	(0.07579)	0.03828	(0.08219)	0.06764	(0.12160)
Net number of products	0.11027***	(0.01822)	0.20917**	(0.08846)	0.22035*	(0.12744)	0.02088	(0.13213)	0.10096	(0.19384)
Number of observations	6,568		1,047		496		3,434		2,883	

Notes: The sample includes only public (listed) firms. See also notes to Table 3, Table 4A and Table 4B in the text. Standard errors clustered at 4-digit industry level (for 4A and Table 3) and firm level (for Table 4B) are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.

Table A.10: Patenting and firm characteristics: Private (unlisted) firms only

	Elasticity to patent stock (Table 3)		Coefficient on patent dummy (Table 4A)				Coefficient on patent dummy (Table 4B)			
			Switchers overall		Around the Switch		Switchers overall		Around the Switch	
<i>Size</i>										
Output	0.14690***	(0.00611)	0.76004***	(0.01516)	0.53283***	(0.01802)	0.45599***	(0.01311)	0.36952***	(0.01240)
Value added	0.14233***	(0.00662)	0.77159***	(0.01628)	0.53923***	(0.01963)	0.44921***	(0.01401)	0.36344***	(0.01344)
Capital stock	0.16484***	(0.00761)	1.03318***	(0.01755)	0.69817***	(0.02198)	0.44902***	(0.01571)	0.36763***	(0.01528)
Employment	0.13285***	(0.00565)	0.57383***	(0.01369)	0.43714***	(0.01633)	0.40195***	(0.01224)	0.33792***	(0.01152)
<i>Factor intensity</i>										
Skill intensity	0.00365***	(0.00107)	0.05064***	(0.00239)	0.03881***	(0.00339)	0.01894***	(0.00223)	0.02216***	(0.00240)
Capital intensity	0.03743***	(0.00601)	0.55371***	(0.01402)	0.33705***	(0.01875)	0.08651***	(0.01253)	0.07649***	(0.01308)
<i>Productivity</i>										
Labor productivity	0.01405***	(0.00312)	0.18621***	(0.00763)	0.09570***	(0.01054)	0.05404***	(0.00681)	0.03160***	(0.00723)
TFP (Solow residual)	0.00275	(0.00243)	-0.00633	(0.00638)	0.00086	(0.00841)	0.02633***	(0.00489)	0.02183***	(0.00515)
OLS-FE (one-step)	0.01178***	(0.00392)	0.10699***	(0.01048)	0.07146***	(0.01474)	0.06993***	(0.00787)	0.04821***	(0.00836)
<i>Scope</i>										
Gross number of products	0.03608***	(0.00322)	0.78750***	(0.00773)	0.51010***	(0.00918)	0.09543***	(0.00690)	0.13187***	(0.00637)
Net number of products	0.03233***	(0.00540)	0.33487***	(0.01023)	0.21857***	(0.01452)	0.01135	(0.00974)	0.04040***	(0.01026)
Number of observations	59,855		30,289		14,886		1,330,529		1,315,126	

Notes: The sample includes only private (unlisted) firms. See also notes to Table 3, Table 4A and Table 4B in the text. Standard errors clustered at 4-digit industry level (for 4A and Table 3) and firm level (for Table 4B) are reported in parentheses; \* indicates significance at 10%, \*\* indicates significance at 5%, \*\*\* indicates significance at 1%.