Demand-pull and technology-push: What drives the direction of technological change?

An empirical network-based approach

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Demand-pull (DP) and technology-push (TP) are drivers of technological change. For policy-makers, it is important to understand how both interact and differ by impact. Using a two-layer network of input-output (market) and patent citations (innovation) links among 307 6-digit US manufacturing industries in 1977-2012, I study two mechanisms of TP and DP: (1) TP and DP are between-layer spillovers when demand shocks in the market pull innovation and innovation pushes growth in the market. (2) Within the same layer, DP arises from downstream links when output users trigger upstream growth, while TP effects spill over from up- to downstream industries. The results support between- and within-layer TP: innovation spillovers from upstream industries drive market growth and innovation. There is also support for within-market TP: positive upstream supply shocks may stimulate market growth, but this effect is heterogeneous across industries. DP is not supported, but the results show that DP forces are associated with a factor bias in favor of labor, while TP comes with a labor demand shift towards non-production work. The results enable a nuanced view on the drivers of technological change and its impact on labor, capital, and productivity. This may inform policy-makers on how to steer the technological evolution.

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Contents

1. Introduction

Shaping the direction of technological change is high on the political agenda to cope with the challenges of the twenty-first century, such as climate change or digitization (IPCC, 2018; Brynjolfsson and McAfee, 2012). Demand-pull (DP) and technology-push (TP) are drivers of technological change (Schmookler, 1966; Myers and Marquis, 1969; Mowery and Rosenberg, 1979; Von Hippel, 1976; Di Stefano et al., 2012) that can be stimulated by different policies (Rosenberg, 1982; Nemet, 2009). Effective policy-making requires an understanding of how these mechanisms interact and differ by their economic impact.

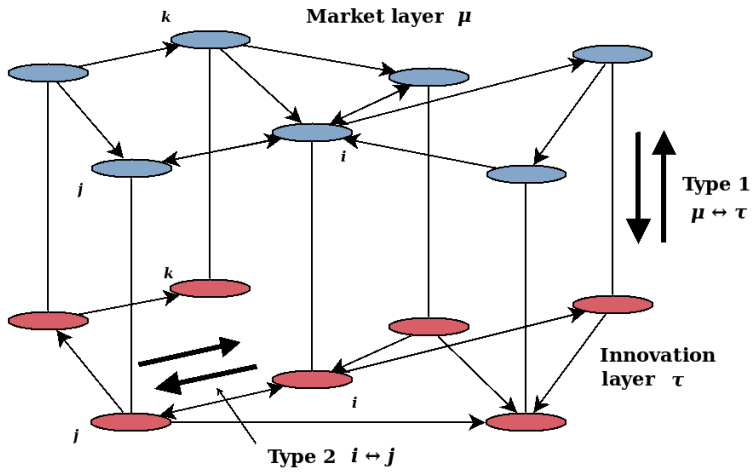
TP arises when technological breakthroughs enable the development and commercialization of novelties. DP emerges from market needs if inventors adapt R&D efforts in response to the perceived market potential (Di Stefano et al., 2012; Von Hippel, 1976). TP and DP are interdependent because R&D objectives can be demand-selected and market needs may arise in response to innovation (Kline and Rosenberg, 1986; Cohen, 2010; Nemet, 2009; Mowery and Rosenberg, 1979; Nelson, 1994; Saviotti and Pyka, 2013).

Here, I study the impact of TP and DP on various indicators of technological change in US manufacturing since the late 1970s. This period was characterized by a qualitative change of industrial production with rising capital intensity and shifts from production to non-production labor with changing skill-requirements (Acemoglu, 2002; Karabarbounis and Neiman, 2014; Elsby et al., 2013). This raised concerns about the decline of the labor share and job market polarization with undesired effects on distribution and employment when low-skill and routine-intensive occupations become obsolete (Baltagi and Rich, 2005; Autor and Salomons, 2018; Goldin and Katz, 2007). Here, I analyze how TP and DP contributed to industry growth, innovation, productivity, and changing production factor requirements.

Previous studies of TP and DP mostly relied on market shares and sizes as proxies for DP and innovation outputs such as patents for TP to study their impact on growth, innovation, and productivity (e.g. Jaffe, 1988; Cohen, 2010). I rely on similar empirical proxies and analyze TP and DP in a two-layer network that captures interactions between markets and innovation.

The network is schematically illustrated in Fig. 1. Industries i, j, k are connected in the top layer, called "market layer" μ (red nodes), by cross-industrial flows of intermediate goods, and in the bottom layer, called "innovation layer" τ (blue nodes), by patent citations. The thick arrows indicate the two conceptually different mechanisms

Figure 1: Stylized representation of the two types of demand-pull and technology-push



Notes: This figure shows the two-layer network of a coupled input-output and patent citation network. Nodes in the network are industries i, j, k and arrows connecting the nodes are flows of intermediate goods in the market layer μ (blue color) and patent citations in the patent layer τ (red color). Demand-pull (DP) and technology-push (TP) Type 1 are between-layer spillovers, while Type 2 are within-layer effects arising from down- and upstream industries.

of TP and DP that are studied in this paper:

Type 1—Between-layer effects: TP1 arises from technological breakthroughs reflected in surges of patenting in the innovation layer ($\tau \to \mu$) and DP1 arises from output shocks in the market ($\mu \to \tau$). TP1 is present if past innovation in an industry i pushes growth in i's market size and DP1 is present if i's market growth pulls innovation.

Type 2—Within-layer effects: TP2 and DP2 are associated with the supply (upstream) and demand (downstream) side of an industry. Within the market, DP2 effects ($j \to i$) are present when spillovers from downstream customers j stimulate growth in upstream industry i. Within innovation, DP2 exists if an increased use of i's inventions in industry j induces further innovation in i. TP2 effects are the opposite ($i \to j$) when changes in the availability of inputs from suppliers i induce downstream technological change in industry j.

These effects are operationalized by network metrics that are empirically calculated using a panel of 307 NAICS 6-digit US manufacturing industries during 1977-2012. The market layer is inferred from empirical input-output (IO) tables provided by the Bureau of Economic Analysis (BEA). The patent citation network is compiled using US

Patent and Trademark Office (USPTO) data and mapped to NAICS 6-digit industries through their technology classes (Goldschlag et al., 2020). The data is supplemented with data on productivity and production factor use (Bartlesman and Gray, 1996; Becker et al., 2013).[1]

Using dynamic panel regressions, I analyze the impact of both types of TP and DP effects on technological change measured by changing industry sizes in both layers (output and patent counts), productivity, and changing use of production factors. Industry sizes inform about the rise and decline of industries, productivity measures the production efficiency (OECD, 2001), and changing factor inputs (employment, wages, capital intensity, share of production labor) inform about the bias of technological change (Acemoglu, 2002). To address cross-industrial heterogeneity in patterns of innovation (Pavitt, 1984), I repeat the analysis of TP and DP for different subgroups of industries and subperiods.

The results support within- and between-layer TP: industries experiencing an expansion of innovation opportunities grow faster in the market (between-layer TP1) and innovate more (within-innovation TP2). These effects mostly arise from innovation spillovers from upstream industries indicating an increase of the technological knowledge base. The support for these two TP effects is remarkably consistent across subgroups of industries and strongest in industries that rely heavily on patented innovation.

The results also support within-market TP2 effects arising from upstream market spillovers, which indicate positive supply shocks in the availability of production inputs. However, within-market TP2 is heterogeneous across industries and upstream network centrality shows a negative effect in some industries. One explanation for the ambiguous role of upstream market linkages relies in their interaction with the position of an industry in the supply chain (cf. McNerney et al., 2022) and a larger process of structural change towards the production of increasingly processed goods (e.g. electronics, machinery, ICT). The results are much stronger during the post-2000s period indicating that TP as driver of change took off at that time.

DP is not supported as a driver of growth and innovation, but I find that downstream linkages in the market are associated with a factor bias in favor of labor. An increasing centrality in the downstream network is associated with a higher labor demand, more investment, a higher productivity, and a lower use of capital.[2] TP effects exhibit the

[1] The data used in this paper is available on request and will be made available upon publication of this paper. An outdated version used for an earlier draft of this paper is available at (Hötte, 2021; Hötte, 2021).

[2] Downstream centrality indicates that an industry supplies goods that are essential inputs in many other industries (who themselves are important suppliers to others). Upstream centrality is an

opposite bias and are associated with a reallocation of labor from production towards non-production activities.

Within the innovation layer, downstream spillovers (DP2) show a weak but statistically significant negative association with innovation. An increasing downstream use of innovations may indicate a higher level of technological maturity and more applied research. The combined results of within-innovation TP and DP effects suggest that technological breakthroughs trickle down the innovation chain from up- to downstream inventive activity.

Finally, the analyses reveal path-dependence of market growth and innovation, which is stronger in the innovation layer with an autocorrelation coefficient larger one. This indicates increasing returns to innovation, which may explain an increasing concentration of innovative activities in a subset of industries.

Four major limitations exist. First, patents as an indicator of innovation suffers from a series of well-known limitations (e.g. Jaffe and De Rassenfosse, 2019; Fontana et al., 2013; Kogan et al., 2017). Second, classification systems change over time, which hampers the study of long-term technology-industry links (Lafond and Kim, 2019; Yuskavage et al., 2007). Third, drivers of technological change differ across firms, industries, time, and industrial maturity (Walsh, 1984; Pavitt, 1984). This heterogeneity may be too complex to be captured by the uniformistic empirical approach used in this paper. Fourth, this research is limited to US manufacturing and neglects other structural changes in the US economy.

Nevertheless, this study offers relevant contributions and insights for research and policy. The two-layer network and the data offer a rich basis for future research that aims to understand how markets and technology interact (see also Sec. 6). This understanding is essential as the societal challenges of today directly interact with technological change: Large scale technological and economic change is necessary to cope with climate change and can be steered by adequate policy (IPCC, 2018). In contrast, digitalization as a process of technological change needs to be steered to alleviate undesirable distributional effects and disruptions in the labor market. These challenges require an understanding of how innovation can be used to influence the evolution of markets for goods and labor, and how market forces can be mobilized to shape technological change.

The results suggest that TP policies that stimulate the creation of technological knowledge may be very effective instruments to influence market growth and innovation. However, the results also show that the distributional effects may be dependent on the

indicator of specialization in upstream industries on few customers.

driver of change. This is important for policy design. For example, it is a long-standing debate whether technology replaces or complements human labor and more recent research raised concerns about job market polarization and an unequal distribution of gains from technological change (see Hötte et al., 2022, for an overview). This research suggests that the driver of change matters: TP shows a bias in favor of capital, while DP dynamics exhibit an opposite relationship. This is informative for innovation policy design when making the choice between DP or TP instruments.

It was also found that innovation is subject to increasing returns. This is important to understand as increasing returns are drivers of endogenous growth (Romer, 1990), which may leverage the effectiveness of innovation policy. However, increasing returns may be also a reason for technological lock-in effects (Arthur, 1989).

The remainder of the paper is structured as follows: The next section provides an overview of the related literature. The theoretical framework is explained in Sec. 3. Sec. 4 introduces the data. Sec. 5 summarizes the results, Sec. 6 offers a discussion, and Sec. 7 concludes.

2. Background

TP and DP as drivers of technological and economic change are the subject of a long-lived debate (Schmookler, 1966; Mowery and Rosenberg, 1979; Pakes and Schankerman, 1984; Cohen, 2010; Saviotti and Pyka, 2013). DP means that R&D follows the market: the perceived commercial potential of innovations offers an incentive for targeted R&D. TP arises from technological opportunities that enable the development of new products and subsequent innovation. The two concepts differ by the assumptions made about the incentives that influence R&D and production decisions, and about the sources of ideas for technological improvements. While DP emphasizes the role of users and customers, TP builds on external and internal research (Cohen and Levinthal, 1989; Kline and Rosenberg, 1986; Di Stefano et al., 2012).

Previous studies found support for both effects (see Cohen, 2010; Di Stefano et al., 2012, for an overview). For example, using aggregate time series over the business cycle, Geroski and Walters (1995) studied interactions between manufacturing outputs and innovative activity. They observed causal effects from outputs to innovation, but no support for the other way round. However, they also highlighted the critical role of stochastic determinants, which they interpret as supply shocks that point to TP from radical innovation. Conceptually in line, Walsh (1984) showed for the chemical industry that TP from radical breakthroughs drives market growth, which creates DP

that induces incremental innovation.

The analysis in this paper is conceptually close to the seminal work by Jaffe (1988) who operationalized DP through the market shares of a firm in different industries and TP as effect that arises from innovation outputs in technologically related fields. The author found that pull and push effects can not be distinguished empirically when explaining TFP growth.

This paper builds on an empirical two-layer network approach composed of an IO and a patent citation layer. The two layers capture the co-evolution of markets and technology (cf. Nelson, 1994), which occurs when market dynamics correlate with innovation (see Saviotti and Pyka, 2013).

Input-output (IO) and patent citation networks can be used to describe technology qualitatively by the network position of an industry, firm, or patent. The position is determined by the bundle of input links pointing to the physical production inputs or pre-existing technological knowledge embodied in patents that enables subsequent innovation. Two firms, industries, or patents are technologically similar if they have many overlapping up- and downstream links, indicating the capability to make use of similar inputs and to serve the needs of similar users (e.g. Carvalho and Voigtländer, 2014; Antony and Grebel, 2012; Acemoglu et al., 2016; Cai et al., 2017; Huang, 2018; Atalay et al., 2011; Jaffe and De Rassenfosse, 2019; Cohen and Levinthal, 2000).

Technological similarity and direct network links enable cross-industrial spillovers of knowledge and market shocks. Other research based on patent data has shown that innovation spillovers may stimulate productivity growth (Antony and Grebel, 2012), innovation (Acemoglu et al., 2016), employment growth and R&D investments (Buerger et al., 2012), and may be a source of path-dependence of technological trajectories (Kay et al., 2014; Taalbi, 2020; Huang, 2018).

In IO networks, the characteristics of an industry's production technology are reflected in the bundle of input used and outputs produced. Other researchers observed that patterns of production input adoption (Carvalho and Voigtländer, 2014) and product market diversification (Boehm et al., 2022) depend on pre-existing IO links. Carvalho (2014) showed that relatedness through IO links can be a moderating factor of output fluctuations.

Here, I combine both types of networks. The mapping from patents to industries proves challenging, but a series of available concordances exist. They mostly rely on the industrial classification of the firms that own patents in specific technological fields (e.g. Kortum and Putnam, 1997; Schmoch et al., 2003; Dorner and Harhoff, 2018; Van Looy et al., 2014; Lybbert and Zolas, 2014; Goldschlag et al., 2020). Concordances make

it possible to study interactions between the evolution of patented technology and industries. Proving the economic validity of their concordance, Goldschlag et al. (2020) showed that industry-technology relationships are relatively stable and changes in the technological composition of industries correlate with occupational change.

This study is not the first that considers the market and innovation network positions simultaneously. Next to Jaffe's (1988) seminal paper, Bloom et al. (2013) build on a similar framework but study the role of market rivalry and knowledge spillovers on firms' performance. Bloom et al. used output linkages to capture rivalry in product markets and patent links to compute knowledge spillovers. They found that market rivalry has a negative on firm performance, while the impact of knowledge spillovers is positive.

3. Technological and economic change in a two-layered network

This section introduces the conceptual framework of the two-layer network, explains how the network is used to identify TP and DP, and introduces the dimensions of technological change that are studied in this paper. It concludes by a short outline of the steps that are undertaken in the empirical analysis.

3.1. The economy as a two-layer network

Technology is the capability to transform a bundle of inputs into outputs. Technological change occurs when the quality and/or quantity of inputs or outputs changes (Saviotti, 1997; Ruttan, 1959). Qualitative information about an industry's technology is revealed by its IO relations in the market and patent citation links. Industries use intermediate goods as production input and build on pre-existing knowledge encoded in other patents to innovate, in addition to production factors such as labor and capital.

Patent citations do not necessarily represent a direct flow of knowledge. Citations in USPTO patents are a legal requirement to describe prior art and to limit the scope of the claims of the new patent. However, a patent citation still serves as an indicator of technological relatedness revealing that the knowledge encoded in the cited patent contributed to the technological basis onto which a patent builds (Jaffe and De Rassenfosse, 2019; OECD, 2009).

The IO and patent citation links span a weighted, directed two-layer network. A node in the network represents an industry $i \in N$, which is connected with other

industries $j \in N$ through patent citations in the innovation layer τ and IO links in the market layer μ, where N is the set of industries in the economy. The layers $\alpha = \mu, \tau$ are linked as a duplex network where each industry has a representation in each layer.

The links in the layers are given by the flow of goods $flow^{\mu}_{ij,t}$ and patent citations $flow^{\tau}_{ij,t}$ from an industry j to i with $i, j \in N$ in time t. These flows reveal two types of information about the technology used by i and j: an input flow from j to i indicates that i has the capability to use the outputs produced by j. It also reveals information about j's capabilities as this industry is able to produce outputs that are valuable for i. Hence, the bundle of upstream (input) links and downstream (output) links reveals qualitative information about the technology that is used in these industries.

Here, the flows of goods and citations are transformed into input shares $w^{\alpha,up}_{ij,t}$ dividing the monetary flow (patent citation count) $flow^{\alpha}_{ij,t}$ by the sum of input flows $\sum_j flow^{\alpha}_{ij,t}$. Analogously, output shares $w^{\alpha,dw}_{ij,t}$ are obtained by dividing $flow^{\alpha}_{ij,t}$ by the sum of all outputs produced by industry i, i.e. $\sum_k flow^{\alpha}_{ki,t}$. Note that $w^{\alpha,up}_{ij,t} \neq w^{\alpha,dw}_{ji,t}$ due to the different weighting. They reflect different concepts: the input share $w^{\alpha,up}_{ij,t}$ reflect j's relevance as an input provider for i while $w^{\alpha,dw}_{ij,t}$ reflect j's relevance as a customer or knowledge user of i. The normalization to shares improves the comparability of different data types (monetary flows, patents) and of industries that are very heterogeneous by size.

Each network layer can be represented as a quadratic, asymmetric $|N| \times |N|$ matrix $W^{\alpha,d}_t = \{w^{\alpha,d}_{ij,t}\}_{i,j \in N}$ with positive non-zero entries if a link from i to j exists in time t. The superscript $d = up, dw$ indicates the direction of the links, i.e. $w^{\alpha,up}_{ij,t}$ ($w^{\alpha,dw}_{ij,t}$) indicates an upsteram (downstream) link. The two-layer network is given by the set of both matrices: one representing the "market layer" and the other presenting the "innovation layer" as illustrated in Fig. 1.

3.2. Network spillovers and centrality

The network data is used to derive a number of network-based indicators to capture up- and downstream TP2 and DP2 effects.

3.2.1. Spillovers

Industries are connected in both layers and shocks in one industry may spill over to industries that are sufficiently close by their up- and downstream linkages (see e.g.

Carvalho and Voigtländer, 2014; Acemoglu et al., 2016; Bloom et al., 2013).[3]

Closeness in networks and spillovers can be empirically captured in different ways. Here, I focus on spillovers from direct up- or downstream links $l_{ij,t}^{\alpha,d} = \mathbb{1}(w_{ij,t}^{\alpha,d} \geq 0.05)$ that equal one if the weight of the link $w_{ij,t}^{\alpha,d}$ exceeds a threshold of five percent and to zero otherwise. Hence, it is assumed that upstream spillovers do only arise from those industries j that are important for i as a supplier and the goods produced by j account for five or more percent in i's input mix. Analogously, downstream spillovers are assumed to arise only from those industries from which i receives at least five percent of its market revenue or patent citations. Spillovers are calculated as

$$Spill(A)_{i,t}^{\alpha,d} = \sum_{j \neq i}^{N} l_{ij,t}^{\alpha,d} \cdot A_{j,t}^{\alpha} \tag{1}$$

with $\alpha = \mu, \tau$, $d = up, dw$. $A_{j,t}^{\tau}$ is the number of patents and $A_{j,t}^{\mu}$ is the amount of goods produced by j in t.[4] Spillovers reveal different information dependent on the layer and whether they emerge from up- or downstream linkages. The level of $Spill(A)_{i,t}^{\alpha,d}$ changes either by an output shock in related industries $A_{j,t}^{\alpha}$ or by a change in the i's up- or downstream network $l_{ij,t}^{\alpha,d}$.

Increasing upstream spillovers in the market suggest that either existing suppliers grow by market size $A_{j,t}^{\mu}$ or that i connected to a new and potentially larger supplier. Analogously, increasing upstream spillovers in the patent layer indicate that the knowledge pool —proxied by patents $A_{j,t}^{\tau}$— of the upstream industry increased or that new sources of patented knowledge were acquired through new citation links. Upstream spillovers are related to TP2 effects as $Spill(A)_{i,t}^{\alpha,up}$ reflects a change in the availability of production and innovation inputs. Generally, high level of upstream spillovers suggests that an industry receives a high share of its inputs from large industries.

Downstream spillovers —in contrast— suggest that an industry's customers grow by market size or new customers were acquired. In the patent layer, $Spill(A)_{i,t}^{\tau,dw}$ indicates that patents by i are either cited by industries with a growing number of patents or by novel groups of knowledge users. Downstream spillovers are indicative for DP2 if they drive technological change in the upstream industry.

[3] For a short discussion of the theoretical foundations of spillovers and the underlying metrics, see Bloom et al. (2013).

[4] Spillovers can be also calculated on the basis of technological similarities. Here, I focus on spillovers from direct links as this is the most direct way to capture the impact of an industry's neighbors in the network and as they show sufficient variation in the innovation layer to disentangle up- and downstream effects (see Sec. 5.2).

3.2.2. Centrality

An industry is central in the network if it is well connected with other industries. Network centrality is an indicator for the relevance of an industry as input provider or output user (cf. Jackson, 2008; Carvalho, 2014).

Different approaches exist to measure network centrality (Jackson, 2008).[5] Here, I use the PageRank $PR_{i,t}^{\alpha,d}$ as centrality measure. It calculated by an recursive algorithm that assigns ranks to industries by the number and quality of links, whereby the quality of a link is higher when it comes from an industry that is itself ranked high by the PageRank (Brin and Page, 1998). I use a version of the PageRank that accounts for the weighted and directed nature of the links (Csardi and Nepusz, 2006).[6]

An industry can be central in two ways: (1) Downstream centrality indicates that an industry is a critical supplier. An increasing downstream centrality in the market (innovation layer) indicates that an industry i became more important as provider of goods (source of knowledge) in the network. This is associated with DP2 in industry i because it reflects an increasing importance of i's outputs that are demanded by downstream industries.

(2) Upstream centrality indicates that an industry is a critical customer. It uses goods or patents that are supplied by a great number of other industries and/ or that account for a large share in their output bundle. If $PR_{i,t}^{\alpha,up}$ increases, the upstream market power of i increases. This may imply a higher diversity of input sources, but it may also reflect a pattern of vertical specialization when upstream industries become more specialized to supply goods to i.

[5] The simplest measure is given by the *degree*, which simply counts the number of different customers (downstream) or input sources (upstream). An industry is more central by the degree if it has more customer (downstream) or suppliers (upstream). The next complex measure is the *strength*, which is a weighted count of in- and output links, i.e. a downstream link receives a higher weight if the input flowing from i to j accounts for a high share in j's input mix. The analogue holds for the upstream strength. An industry i is more central by the strength if it has many customers that receive a high share of their inputs from i.

[6] Originally, the PageRank was developed by Brin and Page (1998) and used in the early versions of the Google search engine to rank websites by their relevance to the users based upstream links that are weighted by the relevance of the websites from which the links are coming. I used the PageRank as centrality measure because it can be computed on the basis of up- and downstream links and shows a sufficiently high variation. Exploratory analyses have shown that the results across different measures are fairly robust and correlation statistics show a high correlation between the PageRank and other measures of network centrality (see A.3).

3.3. Demand-pull and technology-push

Here, I study two different types of DP and TP:

Type 1—Between-layer effects: TP1 is a spillover from patented innovations to the market ($\tau \rightarrow \mu$). DP1 is the opposite: positive shocks in the market trigger patented innovation ($\mu \rightarrow \tau$). In the empirical analyses below (Sec. 5), I interpret all between-layer effects of innovation on the market as TP1. DP1 are all effects that operate in the opposite direction.

Type 2—Within-layer effects: TP2 and DP2 are interactions between up- and downstream industries within the same network layer: TP2 is present when positive shocks in upstream industries j induce technological change in downstream industry i. DP2 is the opposite: Positive shocks in downstream industries i indicate an increasing use of the outputs produced by j (goods and knowledge), and DP2 is present if this induces technological change in the upstream layer.

3.4. Technological change

Technological change is reflected in industrial growth and innovation, and may be associated with qualitative changes in the production function. At the industry level, this is reflected in a changing composition of in- and outputs used for the production of goods and for innovation. This leads to changes in industry sizes: some industries grow, others shrink in relative and absolute terms.

Technological change is also reflected in a changing use of production factors, which is measured by productivity, labor requirements, capital and investment intensity. This *qualitative* dimension of technological change is referred to as non-neutral or directed technological change. In the second part of the empirical analysis, I ask whether and how different types of TP and DP interact with the direction of technological change.

As well known from the literature, patterns of innovation and technological change are heterogeneous across industries (Pavitt, 1984; Kline and Rosenberg, 1986; Cohen, 2010) and may differ over time. Here, I take account of *sectoral patterns of innovation* by analyzing the role of TP and DP separately for different subsets of industries and separately for the first half and the second half of the time periods covered. The second subperiod was characterized by a major trade shock caused by Chinese import competition, which triggered larger disruptions in the US economy (Pierce and Schott, 2016). Splitting the sample by the pre- and post-2000s helps understand whether the drivers of technological change have changed over time.

Wrapping up, in this paper, technological change is analyzed in the following ways:

1. I begin with a descriptive analysis illustrating the rise and decline of industries and show how the characteristics of the networks evolved over time.

2. Next, regressions are used to identify the impact of both types of TP and DP effects on industry growth $A^{\mu}_{i,t}$ and innovation $A^{\tau}_{i,t}$.

3. Then, I analyze the direction of technological change through a series of regressions of productivity indicators (value added per employee $(VA/L)_{i,t}$ as measure of labor productivity, total factor productivity $TFP_{i,t}$), and a series of indicators about the use of different production factors (employment $L_{i,t}$, wages $W_{i,t}$, capital intensity $(K/L)_{i,t}$, investment per capita $(I/L)_{i,t}$, the share of production labor $(L^P/L)_{i,t}$, and the relative wage paid for production labor $(W^P/W)_{i,t}$).

4. Finally, I repeat the analyses for different groups of industries that differ by innovation intensity $(A^{\tau}/A^{\mu})_i$, market size A^{μ}_i, centrality in the patent network $PR^{\tau,dw}_i$, up- and downstream centrality in the market network $PR^{\mu,d}_i$, by broad industry group (defined by their 2-digit NAICS code), and by Pavitt industry group using the coding proposed by Bogliacino and Pianta (2016).

In the next section, I briefly describe the data before I dive into the empirical model specification and the results.

4. Data

The two-layer network is inferred from two different data sets covering the US manufacturing sector during the period 1977-2012. The data is available in five year snapshots. The market layer is compiled with national account data provided by the Bureau of Economic Analysis (BEA). The data is combined with data on patents granted by the US Patent and Trademark Office (USPTO) which are classified by the Cooperative Patent Classification (CPC) system. Using the concordance tables by Goldschlag et al. (2020), 4-digit CPC codes are mapped to industries and aggregated into five year windows in accordance with the IO data (see A.1.2 for more detail). This enables the compilation of a cross-industry patent citation network for different periods.

The networks are given by symmetric matrices where the entries are flows of goods $flow^{\mu}_{ij,t}$ and patent citations $flow^{\tau}_{ij,t}$. The data on cross-industrial flows is harmonized to shares. The networks are used to compile the industry level citation-weighted patent stocks $A^{\tau}_{i,t}$, output $A^{\mu}_{i,t}$, centrality $PR^{\alpha,d}_{i,t}$, and spillovers $Spill(A)^{\alpha,d}_{i,t}$.

The network data is complemented with the Manufacturing Productivity Database from the National Bureau of Economic Research (NBER) and US Census Bureau's Center for Economic Studies (CES) (Becker et al., 2013; Bartlesman and Gray, 1996). From this data, I extracted five factor productivity $TFP_{i,t}$, value added per employee $(VA/L)_{i,t}$ which is used as a proxy of labor productivity, employment $L_{i,t}$, labor costs per employee (hereafter called "Wage") $W_{i,t}$, investment per employee $(I/L)_{i,t}$, capital intensity $(K/L)_{i,t}$, the share of production workers $(L^P/L)_{i,t}$, and the relative wage for production labor $(W^P/W)_{i,t}$ as additional variables.[7] The data in monetary terms ($A^{\mu}_{i,t}$, $VA_{i,t}$, $W_{i,t}$, $W^P_{i,t}$, $K_{i,t}$, $I_{i,t}$) is deflated using the industry level price deflator for the value of shipment from the NBER database.

The final data consists of a balanced panel of 307 6-digit manufacturing industries. More aggregate data is used for additional robustness checks. The most important steps of the data compilation are summarized in A.1. Additional detail is provided in SI.1.

5. Results

This section begins with a descriptive analysis of the two network layers and their overlap. In Sec. 5.2, it follows a series of regressions studying the impact of TP and DP.

5.1. Descriptive analysis

Fig. 2 shows a series of upstream network plots at the 4-digit level for the first and second half of the time period. A link between two industries i and j is shown if the connecting weight $w^{\alpha,up}_{ij,t}$ is strong.

The node sizes are proportional to the scaled industry size in logs $A^{\alpha}_{i,t}$ and the algorithm that generates the plots tends to group industries with similar linking patterns together (see Notes in Fig. 2 or A.2 for technical details). The node colors indicate the broad industry group.

This visual analysis shows a more balanced size distribution of industries in the market compared to the innovation layer, which is strongly dominated by electronics

[7] Production labor includes jobs that are related to tasks like fabricating, processing, maintenance, repair, product development, and similar activities. Non-production labor covers tasks associated with supervision, sales, delivery, advertising, finance, legal issues, and similar services (see https://www2.census.gov/programs-surveys/asm/technical-documentation/questionnaire/2021/instructions/MA_10000_Instructions.pdf).

(blue), machinery (dark violet), and chemical manufacturing (red). The black color captures residual and cross-sectoral economic activities. The large size of black colored nodes ("Other") in the innovation layer is an artifact of the concordance table, as this category captures many patents with CPC codes that are not straightforward to attribute to more specific industries.[8] The comparison over time suggests an increasing concentration in both layers.

In the market layer, groups of industries with similar color tend to cluster together. The position of the clusters interacts with the position in the supply chain ("trophic level" (McNerney et al., 2022)). Industries that are close to more primary resources (food processing (greenish), textiles (yellow)) or close to final consumers (food, textiles, electronics (blue), transportation (gray)) are located at the margins, while chemicals (red), metals (violet) and petroleum products (brown) with intermediate positions in the supply chain between primary input providers and end users take central positions.

This pattern is different in the innovation layer where the largest nodes (electronics (blue), chemistry (red), and machinery (dark violet)) take the most central position suggesting that they are important providers and users of innovations. It is also clearly visible that the electronics sector (including computer industries) grew most strongly over time.

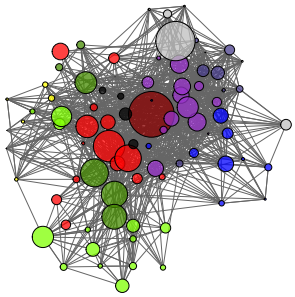
Statistics about the properties of the two network layers (see Table B.2) and about the industry size rankings (Table 1) confirm the visual impressions. Generally, the connectivity in the innovation layer is higher: An industry is connected to roughly 40-50 other industries by patent citations but only 20-30 industries by IO links. While the characteristics of the IO network fluctuate without any clear trend, the innovation layer became increasingly connected and industries became more similar by their patent citation patterns. Both layers show a negatively valued, but stable assortativity: larger and more connected industries tend to be linked to smaller and less connected industries (see B.2).

[8] "Other" includes sectors with the 3-digit NAICS codes 337 and 339, which cover a wide range of residual manufacturing sectors ranging from special types of furniture, medical supplies, buttons, brushes, and miscellaneous other categories that do not fit well into the other 3-digit groups. Many of these industries map to relatively high number of 4-digit CPC codes, which leads to a high number of patents attributed to these industries. The weighting scheme does not fully offset this effect. This does also affect the ranking of industries by patent count (see below in Table 1). An illustrative example offers the sector "Fastener, Button & Pin", which ranks very high by the number of patents. Its NAICS 6-digit code maps to almost 50 different 4-digit CPC codes, which is about five times higher than the average number of CPC links per 6-digit industry. This industry falls into one of the residual categories starting with 33999.

Figure 2: Upstream networks at the 4-digit level for different periods

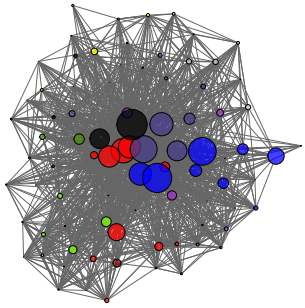
1977-1992

(a) Input-output



Nodes: 85, # Links: 1211

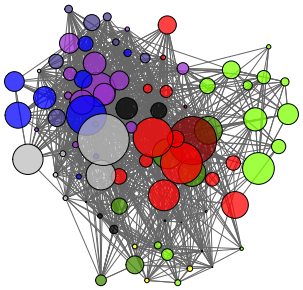
(b) Patent-citations



Nodes: 85, # Links: 1699

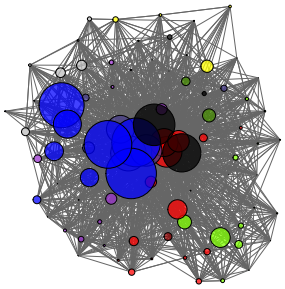
1997-2012

(c) Input-output



Nodes: 85, # Links: 1450

(d) Patent-citations



Nodes: 85, # Links: 1835

Food Textiles Fiber Petroleum Chemicals Metals Machinery Electronics Transport Other

Notes: These figures show the network of upstream links (suppliers) at the 4-digit level for two different time periods. Self-citations and within-sector IO flows are not shown. The colors indicate broad industrial categories given by groups of 3-digit level industries, i.e. Food (311-312), Textiles (314-316), Fiber (321-323), Petroleum (324), Chemicals (325-327), Metals (331,332), Machinery (333), Electronics (334-335), Transport (336), Other (337-339). A link between industries i and j is shown if j is an important supplier to i, i.e. if the average of the weight $w_{ij,t}^{in,\alpha}$ during a subperiod exceeds a threshold level given by the average weight over all industry pairs and both subperiods plus one standard deviation ($\text{mean}(w_{ij,t}^{in,\alpha}) + \text{sd}(w_{ij,t}^{in,\alpha})$). The size of the nodes is proportional to the log size of an industry $A_{i,t}^{\alpha}$. Before taking logs, $A_{i,t}^{\alpha}$ had been scaled by its standard deviation over all industries and time periods. This enables a comparison of sector sizes and their distribution over time and across layers. The figure is generated using the R-package *igraph*, which makes use of the Fruchtermann-Reingold algorithm to allocate the nodes. The algorithm aims to minimize the crossing of links while keeping the length of the links similar. Technical detail is provided in A.2.

Table 1: Top-10 ranking of industries by output and patent stock at the 6-digit level.

Top-10 industries by Aggr. output ($A^{\mu}_{i,t}$)

1977-1982			1987-1992			1997-2002			2007-2012		
324110	Petroleum Refineries	30.55	324110	Petroleum Refineries	17.24	324110	Petroleum Refineries	19.13	334413	Semiconductor	39.65
324199	Petroleum & Coal Prod	8.98	325211	Plastics Material, Resin	8.76	334413	Semiconductor	15.48	324110	Petroleum Refineries	20.15
331111	Iron & Steel Mills	8.28	311611	Animal Slaughter	7.57	331111	Iron & Steel Mills	11.24	334111	Electr Computer	18.98
311611	Animal Slaughter	8.13	324199	Petroleum & Coal Prod	6.43	325211	Plastics Material, Resin	8.13	336112	Light Utility Vhcl	8.03
325211	Plastics Material, Resin	7.36	331111	Iron & Steel Mills	5.56	326191	Plastics Plumb Fixture	4.78	331111	Iron & Steel Mills	7.44
322121	Paper Mills	5.20	322130	Paperboard Mills	5.43	321113	Sawmills	4.73	325211	Plastics Material, Resin	5.36
322122	Newsprint Mills	5.19	322122	Newsprint Mills	5.39	332710	Machine Shops	4.68	336391	Motor Vhcl Air-Cond	4.75
325510	Paint & Coating	4.54	322121	Paper Mills	5.38	334418	Print Circuit Assembly	4.09	336411	Aircraft Mnft	4.27
322130	Paperboard Mills	4.41	325510	Paint & Coating	4.82	311119	Other Animal Food	3.68	336111	Automobile Mnft	4.09
327320	Ready-Mix Concrete	3.82	327320	Ready-Mix Concrete	3.98	322121	Paper Mills	3.61	336350	Vhcl Power Train Parts	3.38
Quartiles:											
0.21, 0.54, 1.11			0.21, 0.65, 1.3675			0.22, 0.545, 1.19			0.28, 0.46, 0.79		

Top-10 industries by Patent stock ($A^{\tau}_{i,t}$)

1977-1982			1987-1992			1997-2002			2007-2012		
325520	Adhesive Mnft	16.23	334413	Semiconductor	19.33	334413	Semiconductor	25.97	334111	Electr Computer	30.12
325998	Misc Chem Prod	15.31	325520	Adhesive Mnft	15.52	334111	Electr Computer	23.77	334413	Semiconductor	29.65
334413	Semiconductor	13.73	334111	Electr Computer	14.87	339112	Surgical & Medical Instr	14.09	339112	Surgical & Medical Instr	15.08
339993	Fastener, Button, Pin	11.62	325998	Misc Chem Prod	14.60	339993	Fastener, Button, Pin	13.60	333314	Optical Instr & Lens	13.34
334111	Electr Computer	9.47	339993	Fastener, Button, Pin	14.00	333314	Optical Instr & Lens	12.48	334510	Electromedical Instr	11.79
333314	Optical Instr & Lens	9.05	333314	Optical Instr & Lens	11.59	325520	Adhesive Mnft	12.33	339993	Fastener, Button, Pin	11.27
333613	Power Transmission Equ	9.01	339112	Surgical & Medical Instr	9.07	325998	Misc Chem Prod	11.48	334518	Watch, Clock, & Part	11.14
333911	Pump & Pumping Equ	6.08	333613	Power Transmission Equ	8.04	334510	Electromedical Instr	11.02	334220	Radio, TV, Communic	11.04
333612	Speed Changer & Gear	5.99	334510	Electromedical Instr	7.61	334518	Watch, Clock, & Part	9.47	325520	Adhesive Mnft	9.98
334518	Watch, Clock, & Part	5.67	334518	Watch, Clock, & Part	6.57	334210	Telephone Apparatus	8.02	325998	Misc Chem Prod	9.23
Quartiles:											
0.0575, 0.33, 0.99			0.06, 0.28, 0.8625			0.06, 0.22, 0.7375			0.05, 0.19, 0.6925		

Notes: Industries are ranked by deflated output (citation-weighted patent stock) $A^{\alpha}_{i,t}$ averaged across the time window indicated in the column header in decreasing order, i.e. showing the largest industries on top. The 6-digit number in the second column of each block shows the NAICS code of the corresponding industry and the third column shows the value of $A^{\alpha}_{i,t}$. The values $A^{\alpha}_{i,t}$ were normalized before through division by the economy-wide average output (patent stock) in t, i.e. the mean value for each period equals one. The bottom lines of each sub-table show the quartile values as indicators for the skewness of the distribution. Deviations of the median from the average indicate skewness.

Table 1 shows the Top-10 ranking of industries by output and patents. Petroleum Refineries (dark red color in the plots) rank persistently at the top position in the market until the 2007 when the first rank was taken over by the semiconductor industry. We can also observe persistently high ranks for Iron & Steel, Plastics Material & Resin, and Semiconductors. Over time, industries associated with natural product processing (Paper Mills, Newsprint, Paperboard, Slaughtering) gradually disappeared from the top ranks. This was accompanied with the rise of machinery and electronics (Machine Shops, Aircraft, Vehicle Air-Conditioning, Automobile).

The top ranks in the innovation layer are dominated by metal, machinery and electronics manufacturing as indicated by the leading 2-digit code 33. Only two chemical industries rank high but declined throughout the time period covered (2-digit code 32). The patent ranks show an increasing dominance of ICT-related industries and specialist instruments (Semiconductors, Electronic Computers, Medical & Optical Instruments, Watch & Clock, Wireless Communication). The time trends in the patent ranking are more monotonous over time, while the rise of Semiconductors (during the 1990s) and Electronic Computers (2000s) came more abrupt in the market as these two sectors did not occupy any of the Top-10 ranks during the decades before. The high rank of the "Fastener, Button & Pin" industry is likely an artifact of the concordance table (see Footnote 8).

The bottom lines in the tables show the quartile distribution of the industry sizes. The data is normalized that the average size in each period equals one. A median value that deviates from one indicates a skewed distribution. Both layers show a skewed distribution with concentration at the top ranks. The table reveals a higher and increasing concentration in the innovation layer while market concentration does not show any clear trend. These observations are consistent across different levels of aggregation (see B and SI.2).

5.2. Demand-pull, technology-push, and technological change

Here, this section presents three sets of results. First, I show the regression results analyzing how different types of TP and DP affect industry growth and innovation. Next, it is analyzed how these drivers interact with the direction of technological change reflected in the use of labor and capital production factors. Finally, I analyze cross-sectoral heterogeneity and summarize the results for different subgroups of industries.

5.2.1. Demand-pull and technology-push

To test the presence of DP and TP, I run the following regressions:

$$Y_{i,t} = \sum_{\alpha=\mu,\tau} \left[\beta_A^{\alpha} A_{i,t-1}^{\alpha} + \beta_{PR}^{\alpha} PR_{i,t-1}^{\alpha,d} + \beta_S^{\alpha,d} Spill(A)_{i,t-1}^{\alpha,d} \right] + \beta' \mathbf{X}_{i,t-1} \tag{2}$$

where $Y_{i,t}$ is a placeholder for $A_{i,t}^{\mu}$ and $A_{i,t}^{\tau}$. The $\mathbf{X}_{i,t-1}$ is a vector of industry level controls explained below. This specification allows to test for both types of TP and DP in the following ways:

Type 1—Between-layer effects: Support for TP1 is found if lagged innovation is positively and significantly related to market growth $A_{i,t}^{\mu}$ reflected in positive coefficients of β_A^{τ}, $\beta_{PR}^{\tau,d}$, and $\beta_S^{\tau,d}$ in the regression of $A_{i,t}^{\mu}$.

Analogously, support for DP1 is found if lagged market dynamics stimulate innovation $A_{i,t}^{\tau}$ reflected in positive and significant coefficients β_A^{μ}, $\beta_{PR}^{\mu,d}$, and $\beta_S^{\mu,d}$ in the regression of $A_{i,t}^{\tau}$.

Type 2—Within-layer effects: TP2 is supported if upstream supply shocks significantly and positively affect downstream growth as reflected in positive coefficients of $\beta_{PR}^{\alpha,up}$ and $\beta_S^{\alpha,up}$ in the regression of $A_{i.t}^{\alpha}$ within the same layer α.

Support for DP2 is found if downstream changes in demand patterns stimulate upstream growth and $\beta_{PR}^{\alpha,dw}$ and $\beta_S^{\alpha,dw}$ show positive and significant coefficients in the regression of $A_{i,t}^{\alpha}$.

A few technical details need to be mentioned. The up- and downstream PageRank in the innovation layer are highly correlated with a correlation coefficient of 98.4% (see Fig. B.1). To avoid multicollinearity, the analysis includes only $PR_{i,t-1}^{\tau,dw}$ but it is not informative about within-innovation DP2. To detect within-innovation DP2 and TP2, I rely exclusively on $Spill(A)_{i,t-1}^{\tau}$.

To deal with unobserved cross-industrial heterogeneity and uniform time trends, the regressions include two-ways time and industry fixed effects (FE). The lagged dependent variables $A_{i,t-1}^{\alpha}$ captures path dependence and industry level time trends in market growth and innovation, that are not driven by the two types of TP and DP under study.[9] Combining lagged dependent variables with individual FE violates

[9] Note that the impact of lagged changes of market size $A_{i,t-1}^{\mu}$ on current market size could be interpreted as an alternative type of within-industry DP effect as an increasing $A_{i,t}^{\mu}$ suggests a higher demand for the products of i. In the innovation layer, the impact of past on current innovation could be seen as an alternative type of TP when own technological breakthroughs

the assumption of strict exogeneity as the demeaning process of the FE causes a correlation of the lagged regressor with the error term (Nickell, 1981). This bias may be non-negligible here as number of time periods is small while the number of industries is large.

The endogeneity can be overcome by using the instrumental variable (IV) approaches proposed by Arellano and Bond (1991) (AB) and Blundell and Bond (1998) (BB). Here, I rely on the system Generalized Method of Moments (GMM) estimator (BB) with robust standard errors for the main results presented in this section.[10]

Market growth and innovation may be also driven by industry-specific structural changes and price shocks that are unrelated to the TP and DP effects studied. A sample of controls $\mathbf{X}_{i,t-1}$ aims to control for these factors. These controls include employment $L_{i,t-1}$, wages $W_{i,t-1}$, capital intensity $(K/L)_{i,t-1}$, the employment share of production labor ($(L^P/L)_{i,t-1}$), relative wages for production labor $(W^P/W)_{i,t-1}$, energy intensity $(E/L)_{i,t-1}$, and material costs per employee $(M/L)_{i,t-1}$. These variables capture the industry-specific and time variant exposure to changes in factor markets, which are not captured by industry and time FE. Further, I control for lagged investment per capita $(I/L)_{i,t-1}$ as it might be the source of an increase in outputs and innovation. To cope with skewness, all variables (except for $(L^P/L)_{i,t-1}$) were first log-linearized and subsequently outliers were removed. The network variables ($A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$) are further scaled by their standard deviation before logs were taken to make them quantitatively comparable. A detailed description of the data transformations is available in A.3.

stimulate subsequent innovation. I refrain from including this effect in the conceptual framework of TP and DP to limit the scope of analysis and discussion of concepts. Instead, I refer to the impact of the autoregressive terms as pure path dependence.

[10] The AB and BB estimator rely on deeper lags as instruments for the lagged dependent variable. The BB specification is chosen because the BB model builds on stronger instruments compared to an AB estimator. It estimates the outcome variable in levels, includes time dummies and it is estimated using a one-step procedure. The one-step method is preferred over a two-step routine for computational reasons. As IVs, I used the maximal number of lags and all exogenous variables. To avoid concerns about instrument proliferation, I re-estimated the model with collapsed IVs as a robustness check. In addition to that, I ran a series of robustness checks using for example deeper lags, one- and two-step estimation procedures and different specifications of the regression equation and empirical variables. The results are qualitatively robust, but sometimes with changing significance levels. Additional results from an AB estimator and a weighted FE regression are available in C.1. The regressions are run using the *pgmm* function of the R-package *plm* (Croissant and Millo, 2008).

Table 2: Demand-pull and technology-push effects.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$ (1)	$A^{\mu}_{i,t}$ (2)	$A^{\tau}_{i,t}$ (3)	$A^{\tau}_{i,t}$ (4)	$A^{\mu}_{i,t}$ (5)	$A^{\mu}_{i,t}$ (6)	$A^{\tau}_{i,t}$ (7)	$A^{\tau}_{i,t}$ (8)	$A^{\mu}_{i,t}$ (9)	$A^{\mu}_{i,t}$ (10)	$A^{\tau}_{i,t}$ (11)	$A^{\tau}_{i,t}$ (12)
$A^{\mu}_{i,t-1}$	0.6255***	0.6073***	0.0035	-0.0058	0.7321***	0.6514***			0.6867***	0.6603***	0.0021	-0.0058
	(0.0291)	(0.0242)	(0.0136)	(0.0127)	(0.0385)	(0.034)			(0.039)	(0.0344)	(0.0128)	(0.0117)
$A^{\tau}_{i,t-1}$	-0.0637	-0.0246	1.034***	1.016***			1.044***	1.034***	-0.0197	-0.0351	1.061***	1.049***
	(0.0947)	(0.0849)	(0.0076)	(0.0068)			(0.0403)	(0.0314)	(0.0862)	(0.0778)	(0.0359)	(0.0303)
$PR^{\mu,up}_{i,t-1}$			-0.0055	-1e-04	0.0066	0.01			0.0088	0.0047	-0.0062	-0.0021
			(0.0046)	(0.0041)	(0.015)	(0.0131)			(0.0145)	(0.0127)	(0.0046)	(0.0039)
$PR^{\mu,dw}_{i,t-1}$			0.0021	0.0041	-0.001	0.0036			-0.0039	0.005	9e-04	0.0039
			(0.0033)	(0.0031)	(0.0145)	(0.0121)			(0.0137)	(0.0118)	(0.0033)	(0.003)
$PR^{\tau,dw}_{i,t-1}$	0.1536**	0.0928*					0.0482**	0.0314*	0.1119**	0.0924**	0.031*	0.0183.
	(0.0478)	(0.0391)					(0.0167)	(0.0136)	(0.0376)	(0.0322)	(0.013)	(0.0109)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0126*	-0.0081	0.1054***	0.1043***			0.0975***	0.0868***	-0.0133*	-0.0088
			(0.006)	(0.006)	(0.02)	(0.0189)			(0.0207)	(0.0195)	(0.0066)	(0.0063)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0044	0.006	-0.0394.	-0.007			-0.0429*	-0.0178	0.002	0.0068
			(0.0058)	(0.005)	(0.0228)	(0.0192)			(0.02)	(0.0181)	(0.0053)	(0.0048)
$Spill(A)^{\tau,up}_{i,t-1}$	2.435***	2.572***					0.7004**	0.3476*	2.363***	2.642***	0.4757**	0.2599.
	(0.7017)	(0.5889)					(0.2131)	(0.1672)	(0.6273)	(0.5391)	(0.156)	(0.1388)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0606	-0.0573					-0.0539***	-0.0369**	-0.0695.	-0.059.	-0.0514***	-0.0378**
	(0.0417)	(0.035)					(0.016)	(0.013)	(0.0369)	(0.0337)	(0.0144)	(0.0126)
AR(1)	0	0	1e-04	2e-04	0	0	7e-04	5e-04	0	0	5e-04	7e-04
AR(2)	0.9373	0.9079	0.899	0.8057	0.9237	0.9583	0.6394	0.7465	0.9656	0.978	0.7307	0.7026
Sargan	0	0	0	0.001	0	0	0	0	0	1e-04	0	0.0056
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9284	0.9354	0.996	0.9962	0.9363	0.9402	0.9952	0.9958	0.9332	0.9374	0.9957	0.996

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^{P}_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The R^2 is proxied by the squared correlation between the fitted and observed values of the dependent variable.

The regression results are presented in Table 2. Even numbered columns show the results when industry level controls $\mathbf{X}_{i,t-1}$ are included. They are not shown here but can be found in C.1.[11]

[11] Among the controls, only wages, investment per capita, and energy intensity enter in a significant way. Wages exhibit a negative association with market growth, energy intensity a negative one with innovation, and investment per capita shows a positive relationship with both market growth and innovation.

The first two columns show the isolated impact of TP1 on market growth. The coefficient of the patent centrality $PR^{\tau,dw}_{i,t-1}$ and upstream innovation spillovers $Spill(A)^{\tau,dw}_{i,t-1}$ enter both with positive and significant coefficients. This observation persists when within layer effects are included (column (9)-(10)). An increase in the normalized centrality by one percent is associated with an 0.1 percent increase in the normalized market size. Innovation spillovers exhibit a quantitatively much stronger effect: A one percent increase is associated with 2.6 percent increase in market size. Note that the network variables $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$ are all scaled to make their coefficients comparable.

The results show that there is no direct effect of within-sector innovation outputs $A^{\tau}_{i,t-1}$ on market growth if controlling for other innovation network effects. However, exploratory analyses have shown that $A^{\tau}_{i,t-1}$ shows a positive effect when other innovation layer effects are excluded. This may be explained by the high correlation between $A^{\tau}_{i,t-1}$ and $PR^{\tau,dw}_{i,t-1}$ while the centrality appears to be the more powerful indicator to explain market growth. Downstream innovation spillovers $Spill(A)^{\tau,dw}_{i,t-1}$ enter with a negative coefficient, which is only weakly significant and becomes insignificant when within-market effects are added (column (10)).

Column (3)-(4) show the isolated effect of DP1 on innovation. None of the market variables ($A^{\mu}_{i,t-1}$, $PR^{\mu,d}_{i,t-1}$, $Spill(A)^{\mu,d}_{i,t-1}$) shows any significant interaction with innovation $A^{\tau}_{i,t}$ suggesting the absence of DP1 effects. This does not change when simultaneously controlling for within-innovation layer dynamics (column (11)-(12)) or altering the model specification (see C.1).

The next two columns (5)-(6) show the results for within-market DP2 and TP2 effects. They offer support for TP2 in the market layer: spillovers from upstream suppliers $Spill(A)^{\mu,up}_{i,t-1}$ enter with a significant positive coefficient. Market growth in upstream industries can be interpreted as a positive supply shock, which is positively correlated with downstream growth. This finding persists when between-layer effects are added (column (12)-(13)). The effect is small: Compared to TP1 arising from innovation in upstream industries, it plays an economically less important role. Within the market, there is no evidence of DP2 effects arising from downstream customers.[12]

Column (7)-(8) inform about the existence of within-innovation DP2 and TP2. The results offer support for TP2: upstream spillovers $Spill(A)^{\tau,up}_{i,t-1}$ enter with a small but positive coefficient. This observation is robust across different estimation methods (AB,

[12] It should be noted that Type 2 effects are not robust if a weighted FE instead of an AB or BB estimator is used. In an FE specification (see e.g. C.5 in C.1) market up- and downstream centrality enter with significant positive coefficients while the effect of spillovers diminishes.

FE) with even more significant effects.

The empirical findings contradict the existence of within-innovation DP2: downstream innovation spillovers $Spill(A)^{\tau,dw}_{i,t-1}$ with a negative coefficient, which is not significant in an AB and weighted FE model (see C.1). Generally, the positive effect of upstream spillovers quantitatively dominates and is about six times higher than the negative effect of $Spill(A)^{\tau,up}_{i,t-1}$.

Beyond TP and DP, the results in Table 2 show that growth in both layers is subject to path dependence: the lagged dependent variable $A^{\alpha}_{i,t-1}$ enters with a positive and strongly significant coefficient. Path dependence is stronger in innovation compared to the market and enters with an autocorrelation coefficient, which is larger than one. One percent more $A^{\alpha}_{i,t-1}$ is associated with approximately 1.05 percent more innovation five years later. The coefficient of $A^{\mu}_{i,t-1}$ scores persistently below one, suggesting a decreasing explanatory power of the autoregressive term over time. This indicates increasing returns to innovation, which is in line with the observation that concentration in the innovation layer grew stronger compared to the market (see Sec. 5.1).

5.2.2. The direction of technological change

This section studies whether and how TP and DP interact with the direction of technological change as being reflected in a changing use of production factors.

This is analyzed through a series of regression analyses showing how productivity, labor demand, capital use, and production labor interact with TP and DP effects arising from both layers. As the dependent variables are not directly associated with one of the two layers, a distinction of within- and between-layer effects is not feasible. Instead, I refer to DP (TP) whenever an effect is driven by the market (innovation) layer. The regression models look similar as above and are given by

$$Y_{i,t} = \beta_Y Y_{i,t-1} + \sum_{\alpha=\mu,\tau} \left[\beta^{\alpha}_{A} A^{\alpha}_{i,t-1} + \beta^{\alpha}_{PR} PR^{\alpha,d}_{i,t-1} + \beta^{\alpha,d}_{S} Spill(A)^{\alpha,d}_{i,t-1} \right] + \beta' \mathbf{X}_{i,t-1} \quad (3)$$

where $Y_{i,t}$ is a placeholder for $TFP_{i,t}$, $(VA/L)_{i,t}$, $L_{i,t}$, $W_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $(L^P/L)_{i,t}$, and $(W^P/W)_{i,t}$. $\mathbf{X}_{i,t-1}$ is a vector of industry level controls explained above.

Table 3: Productivity, labor, capital, and production labor

	Productivity				Labor & Wages				Capital & Investment				Production labor			
	$TFP_{i,t}$	$TFP_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$L_{i,t}$	$L_{i,t}$	$W_{i,t}$	$W_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$A^{\mu}_{i,t-1}$	0.0459**	0.0275.	-0.1465*	-0.1469*	-0.2349***	-0.0895*	-0.2227***	-0.2082***	0.1234***	0.0492*	-0.1769*	-0.1578.	-0.0099*	-0.0149***	-0.0138.	-0.0186*
	(0.0166)	(0.0159)	(0.0624)	(0.0629)	(0.0426)	(0.0438)	(0.0526)	(0.0527)	(0.0216)	(0.0213)	(0.0886)	(0.0923)	(0.0041)	(0.0043)	(0.0072)	(0.0075)
$A^{\tau}_{i,t-1}$	0.0966*	0.0096	-0.1031	-0.0482	-0.4202***	-0.019	-0.0747	-0.0632	0.2042***	0.0924	-0.598*	-0.1016	-0.038***	-0.0265*	-0.0669***	-0.0306
	(0.0452)	(0.0446)	(0.1587)	(0.1675)	(0.1152)	(0.1171)	(0.1337)	(0.1402)	(0.0587)	(0.0568)	(0.237)	(0.2458)	(0.0112)	(0.0115)	(0.0195)	(0.0201)
$PR^{\mu,up}_{i,t-1}$	0.0034	0.0082.	0.042*	0.047*	0.0258.	0.0223.	0.0585***	0.0596***	-0.0017	-0.0048	0.0577.	0.0602*	0.0013	0.0013	0.0068**	0.0069**
	(0.0051)	(0.0048)	(0.0196)	(0.0196)	(0.0142)	(0.0136)	(0.0166)	(0.0164)	(0.0072)	(0.0067)	(0.0294)	(0.0288)	(0.0014)	(0.0013)	(0.0024)	(0.0024)
$PR^{\mu,dw}_{i,t-1}$	0.0063	0.0123**	0.046**	0.057***	0.024*	0.0265*	0.0371**	0.0398**	-0.0027	-0.0096.	0.0629**	0.0619**	-7e-04	-1e-04	-3e-04	0
	(0.0043)	(0.0041)	(0.0162)	(0.0163)	(0.0117)	(0.0112)	(0.0136)	(0.0136)	(0.0059)	(0.0055)	(0.0242)	(0.0239)	(0.0011)	(0.0011)	(0.002)	(0.0019)
$PR^{\tau,dw}_{i,t-1}$	-0.0041	-0.0166	-0.1013	-0.0463	-0.155**	0.0136	0.0284	0.0841	0.1312***	0.0384	0.1126	0.1945.	-0.0026	-0.0064	0.0248**	0.0265**
	(0.0196)	(0.0192)	(0.0734)	(0.0745)	(0.052)	(0.0514)	(0.0619)	(0.0623)	(0.0262)	(0.0252)	(0.1078)	(0.1093)	(0.005)	(0.0051)	(0.0087)	(0.0089)
$Spill(A)^{\mu,up}_{i,t-1}$	-0.0111	-0.0117	-0.0742.	-0.0815*	-0.0743*	-0.0555.	-0.0718*	-0.0672.	0.0424**	0.0319*	-0.0883	-0.1051.	-9e-04	-0.0025	0.0107*	0.0088.
	(0.0103)	(0.0097)	(0.0412)	(0.0411)	(0.0297)	(0.0284)	(0.0348)	(0.0344)	(0.0151)	(0.0139)	(0.0615)	(0.0604)	(0.0029)	(0.0028)	(0.005)	(0.0049)
$Spill(A)^{\mu,dw}_{i,t-1}$	-0.016*	-0.0135*	-0.0161	-0.0176	0.0032	-0.0079	-0.004	-0.0085	-0.0046	-0.0035	-0.0041	-0.0165	-2e-04	7e-04	0.0032	0.0033
	(0.0065)	(0.0062)	(0.0252)	(0.0252)	(0.0181)	(0.0175)	(0.0212)	(0.0212)	(0.0092)	(0.0086)	(0.0376)	(0.0371)	(0.0018)	(0.0017)	(0.0031)	(0.003)
$Spill(A)^{\tau,up}_{i,t-1}$	-0.7711***	-0.7479***	-1.471.	-1.207	-0.754	-0.4783	-1.533*	-1.336*	0.1511	0.0448	0.3971	1.124	-0.2311***	-0.201***	-0.3043**	-0.2156*
	(0.2122)	(0.2002)	(0.7862)	(0.7875)	(0.5666)	(0.5451)	(0.6627)	(0.661)	(0.288)	(0.2676)	(1.174)	(1.159)	(0.0551)	(0.0543)	(0.0961)	(0.0946)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0424*	-0.0225	0.0341	0.0382	0.0839.	0.0322	0.0474	0.0451	-0.0202	-0.0286	0.2051*	0.1815.	0.0043	0.0043	-0.0014	-0.0041
	(0.0176)	(0.0167)	(0.0659)	(0.066)	(0.0478)	(0.0459)	(0.0556)	(0.0554)	(0.0242)	(0.0224)	(0.0988)	(0.0971)	(0.0046)	(0.0045)	(0.0081)	(0.0079)
Controls		Y		Y		Y		Y		Y		Y		Y		Y
R^2	0.7438	0.7746	0.9007	0.9024	0.929	0.9359	0.9251	0.927	0.9135	0.927	0.8259	0.8339	0.8778	0.8832	0.662	0.6776

Notes: The table shows the regression results of productivity, labor demand, capital use, and production labor on demand-pull and technology-push effects. The estimation is based on a two-ways weighted fixed-effects (FE) model. The weights used in the regressions are $A^{\mu}_{i,t}$ in the TFP regression and $L_{i,t}$ in all other regressions. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1.

The regression models again include lagged dependent variables and may be again subject to a dynamic panel bias (Nickell, 1981). This bias may be addressed using a BB or AB estimator as above, but these estimators suffer from weak instruments. Hence, I rely on a weighted FE approach with industry and time FE and two-ways clustered standard errors. The weights in the regression of $TFP_{i,t}$ are the market size $A^{\mu}_{i,t}$ to capture the impact of DP and TP on productivity for an average good produced. For all the other regressions, I rely on employment $L_{i,t}$ as weights to capture the different relevance of industries for the US labor market. Hence, the results inform on how the labor productivity, wage, or capital intensity of an average employee was affected instead of capturing the effect on an average industry.

Results from alternative estimators are reported in C.2. Generally, the findings are qualitatively consistent across the different specifications, sometimes with variation in their statistical significance.

The results are shown in Table 3. To keep it short, I present only the results of the full models that include market and patent layer effects simultaneously.[13] Even numbered columns show the results that include industry level controls $\mathbf{X}_{i,t-1}$, which are not shown here but can be found in C.2.

Columns (1)-(4) show the results for productivity measured as 5-factor TFP and value added per employee. Columns (5)-(8) inform about labor demand as reflected by employment and wages. Columns (9)-(12) show the effects on capital use and investment intensity. The last two columns (13)-(16) show to which extent an industry relies on production and non-production labor.

Consistently across different estimation methods, an increasing downstream centrality in the market $RP^{\mu,dw}_{i,t-1}$ shows a positive association with productivity growth. It further shows a factor bias in favor of labor as it is positively correlated with labor demand and wages (column (5)-(8)), a negatively with capital use (column (9)-(10)), and positively with investments per capita (column (11)-(12)). Quantitatively, the positive impact on investment is about twice as large as the decrease in capital intensity. Market upstream centrality $PR^{\mu,up}_{i,t-1}$ shows similar effects, namely a positive correlation with wages and employment, relative wages for production labor, labor productivity, and investment.

Further, the results suggest that upstream spillovers $Spill(A)^{\alpha,up}_{i,t-1}$ from both layers $\alpha = \mu, \tau$ are associated with a decline in productivity (column (1)-(4)), wages (column (7)-(8)), and a decreasing demand for production labor (column (13)-(16)). These spillovers are positively correlated with a higher capital intensity. This finding is qualitatively robust across different estimators, but not or only weakly significant.

[13] Additional results with separate layers can be found in the SI.3.

Moreover, TP arising from more innovation $A^{\tau}_{i,t-1}$, higher upstream innovation spillovers $Spill(A)^{\tau,up}_{i,t-1}$ and centrality $PR^{\tau,dw}_{i.t-1}$ is associated with a shift from production to non-production labor (columns (13)-(16)) as they both show a positive correlation with the share of production labor $(L^P/L)_{i,t}$ but no significant effect on labor $L_{i,t}$.

Generally, an market growth $A^{\mu}_{i,t-1}$ and more innovation $A^{\tau}_{i,t-1}$ are associated with decreasing employment and wages, a lower share of production labor, and less significantly, with an increasing capital intensity, higher TFP, and lower labor productivity. These observations are qualitatively robust across different estimators but less or not significant in other model specifications.

5.2.3. Sectoral patterns of innovation

Patterns of innovation, technological change, and sources of knowledge differ across industries and may change over time (Pavitt, 1984; Kline and Rosenberg, 1986). To capture this, I repeated these regressions for different subsets of industries and subperiods (1987-1997, 2002-2012).[14] To simplify the representation, I do only verbally summarize the main observations. The regression results for the two subperiods are provided in C.1-C.2, and those for the industry subgroups are available in SI.4.

Table 4 gives an overview of the industry subsets that were analyzed, shows how these subsets were defined, and indicates whether TP and DP are supported. The full mapping of NAICS 6-digit industries to subgroups can be found in Table SI.7. The $*$-symbols indicate support, X-symbols indicate that opposite, i.e. negative effects were found, and $\sim$-symbols suggest that the results were ambiguous across variables and/or model specifications.

Next, I summarize the results in more detail by going step-wise go through the different drivers (TP1, DP1, TP2, DP2) and briefly discuss in which industry groups the effect is supported or not.

TP1: This effect is supported consistently across all subsamples with varying levels of significance. TP1 arises from both, $PR^{\tau,dw}_{i,t-1}$ and $Spill(A)^{\tau,up}_{i,t-1}$, while the effect from upstream spillovers is larger and more significant in most of the subsamples. The effect is statistically and economically most significant during the second subperiod and in Metallic and Machinery manufacturing, Innovation-intensive, Small, Production-intensive sectors, those with a high innovation

[14] Technically, the two subperiods cover the periods 1977-1997 and 1992-2012. They overlap in two 5-year snapshots. However, the overlap does only matter for the first stage of the regressions as the BB estimator uses the second lag as in instrument for the first lag. Hence, the first two periods are lost through the estimation procedure.

Table 4: Overview - Sectoral patterns of innovation

Name	Definition	N	TP1	DP1	$TP2^{\mu}$	$TP2^{\tau}$	$DP2^{\mu}$	$DP2^{\tau}$
All sectors		2456	***		***	*		X
First subperiod	1987-1997	1535	*					
Second subperiod	2002-2012	1535	***		***	***	X	XXX
Food Processing	2-digit 31	520	**					
Non-Metallic	2-digit 32	656	**			**		
Metallic and Machinery	2-digit 33	1280	***	$\sim$	***		X	XX
Innovation-intensive	$> \text{md}(A^{\tau}/A^{\mu})$	1224	***	*		**	$\sim$	XXX
Non-Inno.-intensive	$\leq \text{md}(A^{\tau}/A^{\mu})$	1232	*	X	XX	*	X	X
Big	$> \text{md}(A^{\mu})$	1224		*		*		XX
Small	$\leq \text{md}(A^{\mu})$	1232	**			**	X	XX
Science-intensive	BP (2016)	360						XXX
Supplier-dominated	BP (2016)	840	**				X	XXX
Production-intensive	BP (2016)	1208	***	$\sim$			X	X
Patent-central	$> \text{md}(PR^{\tau,dw})$	1224	***	*		***	X	XXX
Non-Patent-central	$\leq \text{md}(PR^{\tau,dw})$	1232	**	XXX	XXX	*	X	X
Market-central (up)	$> \text{md}(PR^{\mu,up})$	1224		*			X	XX
Non-Market-central (up)	$\leq \text{md}(PR^{\mu,up})$	1232	**			*	XX	X
Market-central (dw)	$> \text{md}(PR^{\mu,dw})$	1224	**	$\sim$	**		X	X
Non-Market-central (dw)	$\leq \text{md}(PR^{\mu,dw})$	1232		X				X

Notes: This table shows how different subsets of industries were named, defined, and it summarizes the results for different push and pull effects. The complete list of how 6-digit NAICS industries are grouped into different subsamples can be found in SI.7. The column N shows the number of observations per sample. The asterisk (X-) symbols ***, **, * (XXX, XX, X) indicate weak, moderate, strong positive (negative) effects by statistical significance and consistency across different model settings. A tilde $\sim$ is shown whenever the effects are ambiguous for different variables that capture the same concept (e.g. qualitative ambiguity between $A^{\alpha}_{i,t-1}$ and $PR^{\alpha,d}_{i,t-1}$). The summary of the results is based on a large sample of regression analyses of different industry subsets and tested for different model specifications. Positive and negative effects are only indicated, if the results are consistent across different specifications. These results will be made available as a comprehensive online Supplementary Material published along with the research data and statistical outputs. A small extract of these results is available in SI.4. The two subperiods (1987-1997 and 2002-2012) technically cover the periods 1977-1997 and 1992-2012. They overlap in two time periods because the first two periods are lost during the estimation method that makes use of the 2nd lag as IV for the first (see also C.1). Food, Non-Metal, Metal are short for the Food processing sector identified by 2-digit NAICS codes 31, Non-metallic (Wood, Fiber, Chemical) manufacturing (2-digit NAICS code 32), Metallic and Machinery manufacturing (2-digit NAICS code 33). Innovation-intensive, Big, Patent and Market central industries are defined by whether or not the corresponding variable taken from the network data and averaged over time ranges above or below the cross-industry median value. The classes Science-intensive, Supplier-dominated, Production-intensive are categories motivated by the taxonomy introduced by Pavitt (1984). The mapping to 6-digit NAICS industries is based on the tables provided by Bogliacino and Pianta (2016) (short: BP (2016)).

network centrality, and those with a low upstream but high downstream centrality in the market.

DP1: Support for DP1 effects is —if present at all— only weakly significant, ambiguous, or even negative; hence market growth, centrality, and spillovers do not show a clearly positive effect on innovation. Generally, but only poorly significant, upstream centrality in the market tends to have a negative effect while downstream centrality rather shows positive effects. The opposite holds for spillovers: Downstream (upstream) spillovers are rather negatively (positively) correlated with innovation.

TP2 in the market: Within the market, upstream spillovers $Spill(A)^{\mu,up}_{i,t-1}$ show a positive association with market growth during the second subperiod, in Metallic and Machinery manufacturing and industries with high downstream centrality in the market. Upstream market centrality $PR^{\mu,up}_{i,t-1}$ shows opposite effects: negative effects are found in sectors with a low innovation-intensity and low innovation centrality.

TP2 in innovation: Upstream innovation spillovers exhibit an unambiguously positive association with subsequent innovation, which is not significant in every industry group. It is significant during the second subperiod, in Non-Metallic manufacturing, Innovation-intensive, Big, Production-intensive sectors, and sectors with a high and low innovation centrality, with a low upstream and high downstream centrality in the market. However, the coefficients are small for Big sectors and those with a low innovation and high downstream market centrality.

DP2 in the market: DP2 from downstream links is not supported. Downstream spillovers enter unambiguously with negative coefficients. Only in Innovation-intensive industries the effect is ambiguous as downstream centrality enters with a weakly significant positive coefficient.

DP2 in innovation: This effect is absent and, whenever a significant effect is observed, the effect is negative contradicting DP2 to be driver of innovation. Almost all industry subsamples show (if they show any effect) a strongly statistically significant but quantitatively small negative correlation between downstream spillovers $Spill(A)^{\tau,dw}_{i,t-1}$ and innovation outputs. This effect is strongest in Metallic manufacturing, Innovation-intensive, Big, Small, Science-intensive, Suppliers-dominated, sectors with a high innovation centrality, and a high downstream market centrality.

Summing up, the results further confirm that the interactions from patents to the market are stronger than vice versa (TP1). The positive interaction from patents to the market mostly arise from upstream innovation spillovers, while up- and downstream connectivity in the market shows ambiguous effects on innovation: downstream spillovers show rather positive interactions with innovation while the opposite holds for upstream effects.

Within the innovation layer, there is clear support for TP2 while the effect of TP2 within the market is ambiguous. The ambiguity within the market largely comes from the qualitatively different impact of upstream centrality and upstream spillovers. Generally, the results suggest that DP2 effects are not supported.

Most of the results are much stronger for the second subperiod of the sample and sometimes not or only very weakly significant in the years.

6. Discussion

The key results can be wrapped up as follows:

1. Both network layers show different dynamics: the innovation layer became increasingly connected, technologically similar, and skewed, while connectivity, similarity, and size rankings in the market are sluggish without a clear trend. The distribution of market shares is more diverse compared to the innovation layer. Both layers show the rise of ICT-related and other electronics industries.

2. The results reveal path-dependence in both layers, which stronger in the innovation layer and indicates increasing returns to innovation. This matches with the observation that innovation became more concentrated than market activities.

3. The results consistently support TP1: past innovation shows a strong positive association with subsequent market growth. TP1 mostly arises from upstream innovation spillovers, which indicate an expansion of the technological knowledge base upon which an industry relies.

   Also the centrality in the innovation network is positively associated with market growth, even though it is less significant. Innovation centrality shows how well an industry's own R&D activity is integrated in the innovation network and informs about an industry's access and exchange of technological knowledge.

4. The results support within-innovation TP2: upstream innovation spillovers appear

to stimulate subsequent innovation. This observation is well in line with previous research (e.g. Acemoglu et al., 2016; Antony and Grebel, 2012; Jaffe, 1986).

5. Within-market TP2 effects are ambiguous. There is support for a positive effect of upstream market spillovers, which is strongest during the second subperiod and in Metallic manufacturing sectors with a high downstream centrality in the market. These spillovers indicate an increased availability of production inputs.

   However, upstream effects in the market are ambiguous and heterogeneous across industries: Upstream market centrality shows a negative effect in industries with a low reliance on innovation.

6. The results do not support DP effects of any type. While DP1 effects are weak and ambiguous across industries, the lack of support of DP2 effects is clear: across almost all industry groups, downstream effects enter with negative coefficients if they are significant at all.

7. Up- and downstream innovation spillovers enter with opposite coefficients, which might be explained by their different meaning. Upstream spillovers inform about the pool of technological knowledge upon which the downstream industry relies. In contrast, downstream spillovers suggest that an industry's own innovations are increasingly used (cited). This may reflect a higher level of technological maturity, which appears to be associated with a lower potential to grow. However, the negative coefficients of downstream spillovers are small and only weakly significant.

8. The analysis in Sec. 5.2.2 indicates that the factor bias of technological change may be dependent on the driver of TP and DP effects. DP arising from a higher centrality in the customer network in the market is associated with higher productivity, more labor demand, and less capital use. This indicates a factor bias in favor of labor, albeit DP does not show any positive effect. In contrast, TP and pure size effects are associated with a lower wages and a reallocation from production to non-production labor.

   Further, TP from innovation spillovers and productivity show a negative correlation, which might be attributed to the shift from production to non-production labor. Previous research has shown that the increasing service share in manufacturing coincided with lower productivity growth, which may be an issue of mismeasurement as intangible capital is difficult to measure (Corrado et al., 2009; Goldin et al., 2022; Baily and Montalbano, 2016; Baumol, 2012).

6.1. Demand-pull, technology-push, and the direction of technological change

The evolution of markets and technology is interdependent and both, push and pull effects can be drivers of change (Kline and Rosenberg, 1986; Saviotti and Pyka, 2013; Mowery and Rosenberg, 1979; Cohen, 2010). Here, TP and DP were conceptualized as between- and within-layer effects.

This analysis suggests that TP from between-layer innovation effects and from within-layer upstream linkages is the key driver of industry growth and innovation in US manufacturing since the late 1970s, especially since the 2000s. A major source of TP are innovation spillovers from upstream industries. The TP from innovation is largest in those industries that rely on patents (Innovation-intensive, high centrality in the innovation layer, Metallic and Machinery manufacturing), and in Small industries, and those with a low upstream, but high downstream centrality in the market. The assignment of individual industries to different subgroups shows a strong overlap of these subgroups (see Table SI.7). Many of these industries that fulfill multiple of these characteristics belong to the group of Metallic and Machinery manufacturing industries.

It is not surprising to find TP driven by innovation to be strongest in those industries, that actually use patents as patents may be unsuited as a measure of technology and innovation in other industries. TP effects driven by non-patented innovations can not be captured by this framework, which is a general limitation of patent-based analyses (see Sec. 6.2 for a discussion of this problem).

These observations are very well in line with the descriptive findings. The post-1980s in the US were characterized by the rise of ICT-related and electronics industries, which largely belong to those industry subgroups that show the positive effect of TP. The rise of these industries was strongest in recent years coinciding with the observation that TP is most significant during the second subperiod.

The analyses suggest that innovation-induced TP comes with a shift from production to non-production labor. Other research documented that the employment effects of recent technological change driven by ICT were heterogeneous across different groups of labor with a positive effect on high-skill, non-routine, and service jobs, but negative effects on low-skilled production workers (see Hötte et al., 2022, for an overview). Other research documented patterns of capital deepening driven by ICT (Corrado et al., 2009). The findings of this paper are well in line with these observations. However, the net impact of TP from innovation on labor markets at the aggregate level cannot be answered by this study, as it analyzes only within-manufacturing effects and ignores

the increasing economic weight of the service sector (Gallipoli and Makridis, 2018).

In contrast to TP, DP does not show any significant positive impact on market growth or innovation, but there is evidence DP arising from customer relationships in the market is associated with productivity growth and labor creating effects. This observation points to the importance of the demand side for the creation of new jobs (Bessen, 2019; Hötte et al., 2022).

Generally, upstream linkages that reflect supply conditions and the availability of technological knowledge and physical production inputs show positive effects on industrial growth, while downstream spillovers show the opposite effect. This finding is similar to the observation made by Bloom et al. (2013) who conceptualized upstream spillovers as positive knowledge spillovers, while downstream spillovers capture negative cannibalization effects. The technical implementation in this paper is different from Bloom et al.'s (2013), but his interpretation bears conceptual similarities. Their concept of market rivalry may be related to downstream market spillovers. The interpretation in the innovation layer is different as downstream spillovers may be associated with technological maturity as discussed above, but there may be also patterns of cannibalization and redundancy when a technology matures.

Another interesting observation is the role of up- and downstream centrality in the market. While upstream centrality tends to show negative correlations with innovation and growth, the opposite holds for downstream centrality. The effects are only weakly significant and matter only in certain subgroups of industries. Nevertheless, this observation is interesting as it points to the relevance of an industry's position in the supply chain. Other research has shown that industries with a deep embeddedness in the supply network tend to grow faster as the positive effects of productivity growth accumulate along the supply chain (McNerney et al., 2022).

In this paper, limitations to data prevented the calculation of output multipliers, which would be the appropriate indicator to capture this. However, the market up- and downstream centrality exhibit similar properties, as industries with a high downstream centrality appear most frequent in sectors that produce highly processed goods (transportation equipment, electronics, chemicals, processed food). Those with a high upstream centrality are more frequently found in sectors that process raw material (mills, raw plastics, primary material processing) (cf. Table SI.7 and SI.2.2). Note that the statistical analyses control for sector FE. Hence, changes in the market up- and downstream centrality reflect whether an industry moved up- or down in the supply chain. It seems that a move down the supply chain is rather positively associated with innovation, market growth, and labor.

6.2. Limitations and research implications

One aspect that was ignored so far is the role of trade. Other research has shown that exposure to import competition from low wage countries may be a driver behind the reallocation from low- to high-tech industries (Bernard et al., 2006). The accession of China to the WTO in 2001 was a large shock to the US manufacturing sector and associated with a sharp drop in US manufacturing employment (Pierce and Schott, 2016). For European countries, Bloom et al. (2016) have shown that Chinese import competition was a driver of technological change inducing the reallocation of production towards more productive firms and spurring innovation within trade exposed firms.

The increased trade exposure of US manufacturing after 2001, can be another explanation for the take off of TP during the second subperiod. However, this study shows that the rise of the ICT sector in innovation was already existent before the 2000s even though the impact of TP was weak and non-existent in innovation. Whether or not the trade-shock caused by the Chinese WTO accession "activated" TP and accelerated the market uptake of the ICT sector and decline of more primary manufacturing activities is beyond the scope of this study.

It should be also noted that this study is limited to manufacturing. Various studies have documented the decline of US manufacturing since the 1980s (e.g. Elsby et al., 2013; Fort et al., 2018). It would be important to verify whether the observed patterns are general or unique for the US manufacturing sector during the four decades covered.

Beyond that, this study is subject to three more technical limitations. First, patents as a measure of innovation are imperfect: the use of patents to protect IP varies across industries (Fontana et al., 2013; Arundel and Kabla, 1998; Cohen et al., 2000), and patents vary greatly by value and not every patent indicates a technological breakthrough (Trajtenberg, 1990; Kogan et al., 2017). Sometimes patents are only filed for defensive purposes to protect a pre-existing, but not a new invention (Granstrand, 1999). Over time citation practices may have changed, not least because of the improved computer-assisted search techniques (Hall et al., 2005; Marmor, 1980). These limitation are partly addressed by restricting the sample to manufacturing where patents are a common means of intellectual property protection (Blank and Kappos, 2012), by controlling for industry and time FE, and by using citation-weighted patents.

Second, studying innovation and industrial evolution over time is challenging because of non-static classification systems (Marmor, 1980; Yuskavage et al., 2007; Lafond and Kim, 2019). This analysis relies on industry codes that are purposely designed to describe industries by their production processes. NAICS is designed as a means for

the description of industries and regularly (quasi-endogenously) updated to meet this purpose. This can be one explanation for the less skewed sector-size distribution, and possibly also for the higher stability of the IO network. In the regressions, I controlled for industry and time FE hoping to capture potential distortions.

Aim of this analysis is the economic study of technological change. This justifies the choice of NAICS codes rather than patent classes. Patents needed to be mapped to industries based on their technological classification. Inferring from patents to industrial dynamics is a challenging endeavor (Antonelli, 2014; Dosi and Nelson, 2010), not least because the industry where a patent is filed is not necessarily the same industry where the patented invention is used. A variety of concordances exist (e.g.. Lybbert and Zolas, 2014; Van Looy et al., 2014; Goldschlag et al., 2020; Dorner and Harhoff, 2018). A systematic, dynamic comparison between these concordances and their implications for economic studies of technological change would be a valuable avenue for future research. It would be also interesting to compare the results of this study with an approach using patent-classes as means of description: classifying IO flows by their correspondence in patent-classes can be insightful to understand the impact of DP on the dynamics of patented innovations. But this is beyond the scope of this paper.

Third, here, I studied TP and DP at the aggregate level. But patterns of innovation, knowledge sources, and IP practices differ across firms, industries, and technology fields (Pavitt, 1984; Carlsson and Stankiewicz, 1991; Blank and Kappos, 2012). Walsh (1984) documented that whether DP or TP dominates may be a matter of industry maturity. The static dimension of sector heterogeneity is captured by the FE approach and by the analysis of various subsamples. But exploring the dynamic dimension of industrial heterogeneity could be an interesting avenue for future work. Walsh (1984) highlighted in a study of the chemical industry that TP from radical breakthroughs may drive growth in the market, which in turn creates DP effects that induce incremental innovation. Future research within a similar methodological framework may take account of the distinction between radical and incremental innovation and the chronology of the technology cycle. This might also confirm whether the results of this study are driven by the ICT sector, which was at a low level of maturity during the early periods under study.

7. Conclusions

Understanding and shaping technological change is a key task for policy-makers in the 21st century. Climate change mitigation requires a dramatic and fast transition to climate-friendly technology (IPCC, 2018) and digitalization may disrupt labor markets with detrimental effects on income distribution (Brynjolfsson and McAfee, 2012; Autor and Salomons, 2018). Understanding the impact of TP and DP as drivers of technological change can help to develop effective policies to steer the process of change and to mitigate undesirable side effects.

Here, I conceptualized TP and DP as between- and within-layer effects and studied their impact on market growth, innovation, and the direction of technological change in an empirical two-layer network of input-output and patent citation relationships between US manufacturing industries.

The results offer strong support for TP suggesting that an increase of the available technological knowledge base can stimulate growth in the market and subsequent innovation. Increasing returns to innovation further suggest that this may be a self-reinforcing process. This provides evidence that R&D policy, that stimulates the creation of relevant technological knowledge, may be an effective instrument to speed up industry level technological change. However, the results also show that technological change driven by TP is factor-biased, which may require supplementary policy to alleviate undesirable distributional effects.

It was also seen that DP tends to show an opposite factor bias, which may help develop political instruments that offset the labor saving effect of TP. The results bear important insights for the debate on whether and how technological change is labor-saving: the results indicate that the factor bias of technological change may be dependent on its driver.

Nevertheless, the results in this study should not be overstated as causal evidence. Many endogeneities can not be overcome and the period under study was characterized by the rise of innovation-intensive ICT-related industries. This paper suggests that TP from innovation and market supply shocks contributed to their rise; but it is hard to say how the observed patterns can be fully extrapolated to other industries and sectors outside of manufacturing. This will be left for future research.

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Appendix

A. Methods

A.1. Data compilation

A.1.1. Input-output data

BEA provides detailed current and historical benchmark IO tables in quinquennial frequency dating back to 1947.[15] I used the most disaggregate data at the 6-digit level. The data is accounting data, which show monetary flows between industries including final demand, and dummy positions that ensure the financial closure. Accounting positions are largely but not perfectly compatible with NAICS or Standard Industrial Classification (SIC) codes. I converted the data step-wise into a time-consistent and convenient format. First, I transformed the data from accounting positions into industry codes, i.e. SIC codes for the 1977-1987 data and into NAICS for later periods. The industry codes are harmonized to the NAICS 2002 version using multiple concordances provided by BEA.[16]

After harmonizing the data, I obtained for each period a matrix of monetary flows between 1179 distinct 6-digit NAICS industries. The entries of the matrix are input flows $flow^{\mu}_{ij,t}$ indicating the monetary value of the inputs that i buys from j in time t. Division of the flows by the row sums $\sum_j flow^{\mu}_{ij,t}$ gives the input shares $w^{\mu,up}_{i,t}$. The output shares $w^{\mu,dw}_{i,t}$ are obtained by division by column sums. Note that some rows and columns are empty for some t. This results from the harmonization procedure to uniform NAICS codes and can happen when the classification changes. Industries can emerge or disappear over time. For example, industries associated with computer technologies were less granular in the 70s compared to the 90s. This is often associated with a split (merge) of pre-existing industries.

A.1.2. Patent data

The patent citation layer is taken from a data set compiled for an earlier project (Hötte et al., 2021; Hötte et al., 2021). The data contains a list of USPTO patents including

[15] The data was downloaded from https://www.bea.gov/industry/benchmark-input-output-data and https://www.bea.gov/industry/historical-benchmark-input-output-tables [Both accessed in Oct 2021].

[16] Detailed explanations of conceptual and technical issues (e.g. changing classification systems, ambiguous mappings) that arose during the compilation are available in SI.1.1.

the grant year and CPC technology classes relying on the USPTO Master Classification File from January 2020.[17] This file offers a list that maps individual patents to one or more CPC classes at the most disaggregate level.

To obtain NAICS level patent data, I merged the patents-to-CPC and the CPC-to-NAICS provided by Goldschlag et al. (2020). The latter is a probabilistic mapping and comes along with probability weights whenever the one CPC class maps to multiple NAICS. These weights are used when compiling industry level patent stocks and industry-to-industry citation counts. To compile the 5-year snapshot of patent stocks, I aggregated weighted patents per NAICS class for each time window. To obtain the number of patents of an industry i and in time t, all patents of a given CPC 4-digit that show a link to NAICS 6-digit sector i are summed up after having been multiplied with the corresponding weight. For example, patents classified into CPC class A01B map to NAICS 6-digit sector 115112 with a weight of 0.9996819 and to sector 237010 with a weight 0.0003181. Hence, all patents that were granted in time window t and classified by A01B were summed up to get the patent count, then multiplied by 0.99996819, and assigned to sector 115112. Industry 115112 does also map to other CPC 4-digit classes (A01C, A01G, E01H). The patent counts from these classes are summed up in the same way and added to the industry level patent count.[18] Note that the number of CPC codes per patent are very heterogeneous, which may lead to double counts. Here, the heterogeneity is ignored as a higher number of co-classifications is often coinciding with a higher value of the patent (Lerner, 1994). This may justify that the patent enters the aggregate data with a higher weight compared to patents with fewer CPC codes.[19]

I used the time windows prior to the benchmark year. For example, for the patent stock in 1977, all patents granted in 1973-1977 are summed up. However, one could also argue to use the subsequent time window 1977-1981 to compile patents for 1977. The IO data is a time snapshot of the last year in the time window. Here, I used time window that precedes the year of the IO data for four major reasons: (1) I used granted patents and the time lag between patent application and grant often accounts for a few years. (2) Innovation is a dynamic concept comprising the process of invention, innovation and commercialization, and diffusion. Using the earlier time window takes account of the diffusion lag. (3) Patents are seen as a proxy for the stock of available

[17] https://bulkdata.uspto.gov/data/patent/classification/

[18] The research data and the R-code used to compile the data are available on request and will be made available upon publication of the final paper.

[19] It should be noted that the final analyses rely on citation-weighted patents, which may lead to a repeated double counting when patents map to multiple CPC classes and are frequently cited. However, the non-citation-weighted and the weighted patent stock are very high (see Fig. B.1).

technological knowledge and patents that will be granted in future are not yet available as knowledge for current use. (4) This approach is consistent with other research where discounted patent stocks were used as proxies of innovation and technological knowledge (e.g. Antony and Grebel, 2012; Huang, 2018).

The same procedure is applied to the citation data, where both the citing and the cited patent both are mapped to NAICS codes. In numbers, more than 37.66 M citation links between 3.75 M individual patents are first expanded to the CPC 4-digit level and then aggregated into citation counts for each NAICS-to-NAICS pair in the relevant time period.

These NAICS-to-NAICS citation counts are transformed into a symmetric matrix where the entries $flow^{\tau}_{ij,t}$ correspond to the flow of citations from i to j, i.e. the number of times that i cites patents from industry j. As above, the entries of $flow^{\tau}_{t}$ are transformed into input shares $w^{\tau,d}_{ij,t}$ through division by the row sum $\sum_j flow^{\tau,d}_{ij,t}$. Output shares $w^{\tau,dw}_{i,t}$ are obtained by division by column sums. Additional detail on the data processing is provided in SI.1.2.

A.1.3. Supplementary data and processing

The data is supplemented with data from the NBER-CES Manufacturing Productivity Database (Becker et al., 2013; Bartlesman and Gray, 1996).[20] For the main analyses, I used 6-digit level data and the subset of manufacturing industries. More aggregate level and additional data on non-manufacturing sectors have been used in earlier exploratory analyses and validation tests.[21] Robustness checks with more aggregate data aim to cope with concerns about the reliability of the classification approach, as classification systems change over time and many sequential transformations were necessary.

The data is unbalanced panel data, i.e. some industries have no data entry for output flows or patent counts in some periods. For the main analysis, industries with incomplete coverage were removed. The final data is characterized by $A^{\alpha}_{i,t} > 0 \ \forall \ t, \alpha$. This reduces the sample size from 473 to 307 6-digit manufacturing industries. All variables that are measured in monetary terms are deflated using the price deflator for the value of shipment (*piship*) from the NBER-CES productivity database.

Both networks (cross-industrial flow and share matrices) and the raw patent data are used to construct industry level variables. Using the raw patent data, I compiled aggregate citation-weighted patent stocks $A^{\tau}_{i,t}$ at the industry level. The citation

[20] https://www.nber.org/research/data/nber-ces-manufacturing-industry-database
[21] The data is available in the accompanying research data publication.

weights are used to control for the heterogeneity of patents by value (e.g. Jaffe and De Rassenfosse, 2019).

Using the IO flow network, I extracted the sum of output given by the column sum $A^{\mu}_{i,t} = \sum_k flow^{\mu}_{ki,t}$ as measure for the market size. To cope with potential inconsistency across time, additional robustness checks are made with normalized data dividing all entries by the cross-industry average $\frac{1}{|N|}\sum_j A^{\alpha}_{j,t}$ for each t. The normalized size measures the size relative to other industries in t and is used to illustrate the evolution of size ranking of industries over time (see Sec. 5.1). In the normalized data, the cross-industry average equals one.

The networks $W^{\alpha,d}_t$ are used to compile the network centrality $PR^{\alpha,d}_{i,t}$. Other centrality measures (degree, strength) are used for robustness checks.

The weight matrices $W^{\alpha,d}_t$ are further used to compute the cosine similarity matrices $\Sigma^{\alpha,d}_t = \{\sigma^{\alpha,d}_{ij,t}\}_{i,j\in N}$ using a sparsity-robust version by Cysouw (2018). The similarity matrix is used to show how technological similarities in the network evolved (see below and Table B.2). The matrices $W^{\alpha,d}_{i,t}$ and industry sizes $A^{\alpha}_{i,t}$ are used to compute cross-industry spillovers $Spill(A)^{\alpha,d}_{i,t}$.

In the robustness checks at other aggregation levels, all measures are re-compiled from the network data at the respective aggregation level as network properties (e.g. centrality, density, clustering) may change in an unsystematic way when the aggregation level changes (Kymn, 1990).

A.2. Network plots

In the network plots shown in Sec. 5.1, links between two industries i and j if j is a sufficiently important input supplier to i and the weight $w^{\alpha,up}_{ij,t}$ exceeds a threshold level defined by the average of weights across all industry-pairs and time periods plus one standard deviation.

The node size is scaled proportionally to $A^{\alpha}_{i,t}$, which is the average value over the time window. To make the sizes in the market and innovation layer comparable, the average value is normalized by division through the cross-industry standard deviation over the full time horizon. After this normalization, the log is taken using a $log(1+x)$ formula to deal with < 1 values.

The plots are generated using the plotting function of the *igraph* package in R using the Fruchtermann-Reingold algorithm for the layout. This algorithm bases on the principle to minimize the number of crossing edges while keeping them at more or less equal lengths. This comes with the side effect that nodes with similar linking patterns

tend to group together.

A.3. Data transformations

Before performing the statistical analyses, a series of data transformations was undertaken to harmonize the data by scale and to cope with outliers and skewness. Table A.1 shows an overview of the variables included in the regression analyses. The columns at the left hand side show the raw data values and the right hand side columns show the values after a series of data transformations that are done to make the data more comparable and to cope with outliers and highly skewed distributions. The transformation steps include in sequential order:

1. Network variables are scaled by their standard deviation to make the size $A^{\alpha}_{i,t}$, centrality $PR^{\alpha,d}_{i,t}$, and spillovers $Spill(A)^{\alpha,d}_{i,t}$ comparable across the three variables and across the two layers.

2. All variables except for the share of production labor $((L^P/L)_{i,t}$ transformed to log values using the formula $\log(1+x)$ to cope with < 1 values. The log-linearization is done to cope with highly skewed data.

3. Outliers are removed according a an interquartile range (IQR) based formula. Those values are treated as outliers that are beyond the 25/75% quantile values minus/plus $(a \cdot IQR)$ with $a = 30$ in the baseline models. Robustness checks are made with more restrictive (i.e. $a = 5$ and $a = 10$) removal rules. The regression results are qualitative consistent with the baseline.

The full code that was used to compile and process the data will be made available upon publication of this paper.

Table A.1: Overview statistics of regression variables

	Before transformation				After transformation			
	Mean	Min	Max	Median	Mean	Min	Max	Median
A_i^{τ}	2557	0.05	141771	504.30	5.873	0.05	11.86	6.22
$A_{i,t}^{\tau*}$	47145	0.02	2741069	6722.00	8.445	0.02	14.82	8.81
$A_{i,t}^{\mu}$	5447	0.30	480728	2498.00	7.594	0.26	13.08	7.82
$A_{i,t}^{\mu*}$	5862	0.36	698224	2870.00	7.726	0.31	13.46	7.96
$PR_{i,t}^{\tau,up}$	0.0033	0.00	0.0699	0.00	1.056	0.40	4.261	0.79
$PR_{i,t}^{\tau,dw}$	0.0033	0.00	0.0697	0.00	1.058	0.40	4.258	0.82
$PR_{i,t}^{\mu,up}$	0.0033	0.00	0.2095	0.00	1.016	0.40	5.349	0.74
$PR_{i,t}^{\mu,dw}$	0.0033	0.00	0.1344	0.00	1.084	0.40	4.908	0.83
$Spill(A)_{i,t}^{\tau,up}$	646738	197324.00	1321936	543613.00	4.064	3.03	4.892	4.01
$Spill(A)_{i,t}^{\tau*,up}$	12140991	3280630.00	28901043	9762547.00	6.941	5.80	7.969	6.88
$Spill(A)_{i,t}^{\mu,up}$	477533	-129887.00	2505736	350955.00	3.587	-2.64	5.528	3.59
$Spill(A)_{i,t}^{\mu*,up}$	537552	-134443.00	2505413	435077.00	3.753	-2.67	5.528	3.80
$Spill(A)_{i,t}^{\tau,dw}$	271075	-9.07	1367711	144102.00	2.352	-0.00	4.926	2.73
$Spill(A)_{i,t}^{\tau*,dw}$	4989650	-124.90	29603733	2218575.00	4.574	-0.01	7.993	5.41
$Spill(A)_{i,t}^{\mu,dw}$	232683	-30240.00	3479138	88113.00	2.217	-1.39	5.855	2.28
$Spill(A)_{i,t}^{\mu*,dw}$	258969	-113022.00	3175549	106248.00	2.343	-2.51	5.764	2.45
$TFP_{i,t}$	4.136	0.04	326.2	0.96	0.6717	0.04	2.428	0.67
$(VA/L)_{i,t}$	105.1	10.46	2404	75.76	4.353	2.44	7.785	4.34
$(VA/L)_{i,t}^{*}$	4053	19.62	366784	1995.00	7.615	3.03	12.81	7.60
$L_{i,t}$	36.43	0.74	469.5	22.67	3.197	0.55	6.154	3.16
$W_{i,t}$	29.85	5.42	101.4	27.85	3.309	1.86	4.629	3.36
$W_{i,t}^{*}$	1278	9.38	84494	687.90	6.548	2.34	11.34	6.54
$(K/L)_{i,t}$	117.2	5.15	1958	75.10	0.6649	0.05	3.025	0.56
$(K/L)_{i,t}^{*}$	4506	33.45	222749	2110.00	3.15	0.29	7.709	3.10
$(I/L)_{i,t}$	7.125	0.20	221.6	4.42	1.774	0.18	5.405	1.69
$(I/L)_{i,t}^{*}$	276.4	1.10	12254	123.00	4.829	0.74	9.414	4.82
$(L^P/L)_{i,t}$	0.716	0.29	0.931	0.74	0.5378	0.26	0.658	0.56
$(W^P/W)_{i,t}$	1.226	0.86	2.581	1.17	1.226	0.86	2.581	1.17
$(W^P/W)_{i,t}^{*}$	0.858	0.48	1.195	0.87	0.858	0.48	1.195	0.87
$Vship_{i,t}$	240.2	20.16	10509	158.50	5.097	3.05	9.26	5.07
$Vship_{i,t}^{*}$	8939	33.80	565041	4149.00	8.366	3.55	13.24	8.33
$(M/L)_{i,t}$	135.8	5.59	9122	77.90	4.412	1.89	9.119	4.37
$(M/L)_{i,t}^{*}$	4575	37.19	322902	2025.00	7.649	3.64	12.69	7.61
$(E/L)_{i,t}$	5.183	0.12	160.6	2.06	1.323	0.12	5.085	1.12
$(E/L)_{i,t}^{*}$	152.9	0.47	7031	58.73	4.143	0.38	8.858	4.09

Notes: This table shows the overview statistics of the variables included in the regression equations before and after data transformation. The last block of rows shows the data entries of the patent counts when the data is not weighted by patent citations. * indicates that the row entry refers to the citation-weighted value for patents and deflated data for market data in monetary terms.

B. Additional descriptive information

Table B.2 shows the properties of the two network layers constructed on the basis of up- and downstream links. In addition, the bottom part of the table shows the network characteristics of the up- and downstream similarity network. This is a network that shows industries as being connected if they are very similar by their bundle of upstream (or downstream) links.

Upstream similarity in the market $\sigma_{ij,t}^{\mu,up}$ indicates that a pair of industries relies on a similar bundle of intermediate goods as production inputs. An increase in $Spill(A)_{i,t}^{\mu,up}$ indicates a rise in the competition for these inputs as either, competitors that use the same inputs grew ($A_{j,t}^{\mu} \uparrow$) or the extent to which input requirements overlap increased ($\sigma_{ij,t}^{\mu,up} \uparrow$).

Downstream similarity in the market $\sigma_{ij,t}^{\mu,dw}$ measures the overlap of i's and j's customer links, which indicates that the outputs of i and j serve similar customer needs. This can be also an indicator for competition if the outputs produced by i and j are substitutes, but it may also indicate demand synergies if the outputs are complements. An increasing similarity of two industries over time may be an indicator of technological and economic convergence.

The first lines of each section of the table show the network density, which measures the connectivity. It shows the ratio of actual over potential network links. Both layers are sparsely connected. The innovation layer is denser and shows an increase in the up- and downstream density over time, while connectivity in the market does not exhibit any clear trend. The average degree (second line of each block in the table) indicates the average number of industries to which an industry is connected. On average, an industry is connected to 20-30 customers and suppliers in the market and cites patents from 44-51 other industries. Both network layers show a negatively valued assortativity: larger and more connected industries tend link more often to smaller and less connected industries.

The density in the cosine similarity networks is an indicator of technological convergence measuring whether or not industries became more similar on average. In line with the connectivity trends, similarity in the market fluctuates without any clear trend, while industries became increasingly similar by patent citations.

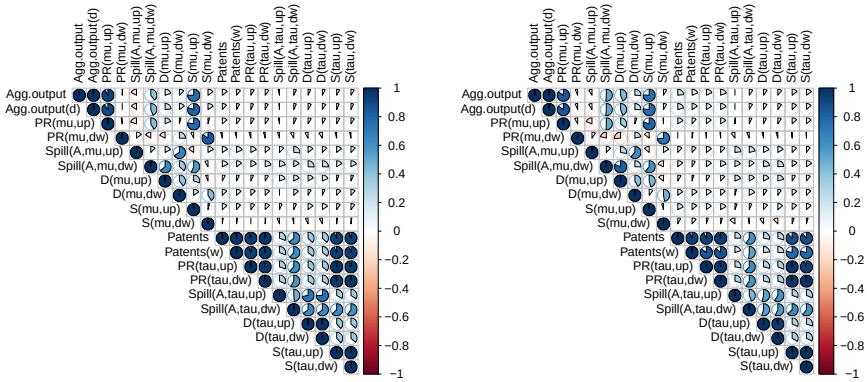
Figure B.1 shows the pairwise correlation of different indicators used to describe the network across and within layers. The figure illustrates a that patent up- and downstream network properties are by far higher correlated compared to the equivalent metrics in the market. The correlation among the network metrics in the innovation

Table B.2: Aggregate network statistics over time at the 6-digit level.

	Input-output				Patent			
	1977-1982	1987-1992	1997-2002	2007-2012	1977-1982	1987-1992	1997-2002	2007-2012
Flow matrix - upstream network								
Density	0.07	0.07	0.07	0.10	0.14	0.15	0.16	0.17
Avg. degree	22.02	21.86	20.08	29.02	44.43	46.39	49.84	51.33
Avg. weight	0.87	0.83	0.88	0.75	0.36	0.35	0.34	0.34
Reciprocity	0.15	0.14	0.12	0.33	0.36	0.34	0.32	0.29
Transitivity	0.34	0.34	0.30	0.34	0.42	0.43	0.45	0.46
Diameter	3.00	3.00	4.00	2.00	2.00	2.00	2.00	2.00
Mean dist.	1.43	1.41	1.43	1.49	1.07	1.04	1.02	1.02
Assort. by degree	-0.25	-0.24	-0.19	-0.33	-0.12	-0.10	-0.07	-0.06
Assort. by size	-0.00	-0.02	-0.03	-0.02	-0.02	-0.01	-0.00	-0.00
Flow matrix - downstream network								
Density	0.08	0.07	0.07	0.09	0.14	0.15	0.16	0.16
Avg. degree	24.15	22.50	20.91	28.39	43.72	45.42	48.95	50.33
Reciprocity	0.17	0.17	0.13	0.30	0.36	0.35	0.33	0.30
Cosine similarity - upstream network								
Density	0.28	0.27	0.28	0.31	0.38	0.40	0.40	0.40
Avg. degree	86.33	83.22	85.20	94.89	116.73	121.32	122.52	123.42
Avg. weight	12.84	11.60	12.20	9.37	23.69	26.35	28.40	31.50
Transitivity	0.67	0.68	0.75	0.63	0.72	0.74	0.75	0.74
Cosine similarity - downstream network								
Density	0.25	0.24	0.23	0.29	0.39	0.40	0.41	0.41
Avg. degree	76.85	73.10	71.95	88.92	118.84	121.95	124.19	125.52
Avg. weight	9.59	8.82	7.72	9.47	25.35	26.52	29.41	30.93
Transitivity	0.61	0.62	0.58	0.67	0.72	0.74	0.74	0.73

Notes: The upper part of the table shows a series of network statistics compiled at the basis of the up- and downstream links in the market- and innovation layer for different time windows. The links in these time windows are averaged. The lower parts of the table summarize the network characteristics of the cosine similarity network given by the symmetric $|N| \times |N|$ cosine similarity matrix $\Sigma_t^{\alpha,d}$ where the pairwise similarities $\sigma_{ij,t}^{\alpha,d}$ are the weights of a link connecting i and j. The metrics are compiled using the R-package *igraph* (Csardi and Nepusz, 2006). For an introduction to the use of these metrics see also Jackson (2008). Those variables that are identical for the up- and downstream network are shown only once. They are identical because of the normalization of weights (Avg. weight) to shares or by the nature of the data (Diameter, Transitivity, Mean distance, Assortativity).

Figure B.1: Pairwise correlations of network indicators in two subperiods



(a) 1977-1992 (b) 1997-2012

Notes: These figures show a correlation plot between different pairs of network variables at the 6-digit level. Figure B.1a (B.1b) shows the average correlations during the first (second) half of the period that is studied. To calculate the average correlations, the data is averaged over the respective time periods before the correlation coefficient is computed. PR is short for PageRank, D for degree, S for strength. $Patents(w)$ is the weighted patent stock. The correlation at the diagonal is by definition equal one. The colors and the shape of the ellipses indicate the strength of correlation.

layer is always positive, while there are some negative correlations in the market, e.g. between the up- and downstream centrality or upstream spillovers and market size. The figure also shows that the correlation patterns are fairly robust over time when comparing the two subperiods.

C. Additional regression results

C.1. Demand-pull and technology-push

Table C.3 show the same results as discussed in Sec. 5.2.1 but including industry level controls. Most of the coefficients of the controls are not significant suggesting that these effects are likely already captured by the FE or the autoregressive term. Only wages, investment per capita, and energy intensity enter in a significant way. Wages exhibit a negative association with market growth, energy intensity shows a negative one with innovation, and investment per capita shows a positive relationship with both market growth and innovation.

Table C.4 and C.5 show the results using an AB and a weighted FE regression. The weights in the FE regression are output for the regression testing the impact of TP and DP on market growth $A^{\mu}_{i,t}$ and citation-weighted patents for the regression assessing the impact on innovation $A^{\tau}_{i,t}$.

Table C.6 and C.7 show the results for the two different subperiods. The data of the subperiods is technically taken the six 5-year snapshots covering 1977-1997 and 1992-2012. This leads to an overlap of two time observations (1992 and 1997) in the estimation procedure. The BB estimator makes use of the second time lag of the dependent variable to build an instrument for the first lag of the dependent variable (Blundell and Bond, 1998; Roodman, 2009). This leads to an exclusion of the first two observations. Hence, the second stage models for the two subperiods do not overlap in time and effectively cover the period from 1987-1992 and 1997-2012.

Table C.3: Demand-pull and technology-push effects including controls.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$ (1)	$A^{\mu}_{i,t}$ (2)	$A^{\tau}_{i,t}$ (3)	$A^{\tau}_{i,t}$ (4)	$A^{\mu}_{i,t}$ (5)	$A^{\mu}_{i,t}$ (6)	$A^{\tau}_{i,t}$ (7)	$A^{\tau}_{i,t}$ (8)	$A^{\mu}_{i,t}$ (9)	$A^{\mu}_{i,t}$ (10)	$A^{\tau}_{i,t}$ (11)	$A^{\tau}_{i,t}$ (12)
$A^{\mu}_{i,t-1}$	0.6255***	0.6073***	0.0035	-0.0058	0.7321***	0.6514***			0.6867***	0.6603***	0.0021	-0.0058
	(0.0291)	(0.0242)	(0.0136)	(0.0127)	(0.0385)	(0.034)			(0.039)	(0.0344)	(0.0128)	(0.0117)
$A^{\tau}_{i,t-1}$	-0.0637	-0.0246	1.034***	1.016***			1.044***	1.034***	-0.0197	-0.0351	1.061***	1.049***
	(0.0947)	(0.0849)	(0.0076)	(0.0068)			(0.0403)	(0.0314)	(0.0862)	(0.0778)	(0.0359)	(0.0303)
$PR^{\mu,up}_{i,t-1}$			-0.0055	-1e-04	0.0066	0.01			0.0088	0.0047	-0.0062	-0.0021
			(0.0046)	(0.0041)	(0.015)	(0.0131)			(0.0145)	(0.0127)	(0.0046)	(0.0039)
$PR^{\mu,dw}_{i,t-1}$			0.0021	0.0041	-0.001	0.0036			-0.0039	0.005	9e-04	0.0039
			(0.0033)	(0.0031)	(0.0145)	(0.0121)			(0.0137)	(0.0118)	(0.0033)	(0.003)
$PR^{\tau,dw}_{i,t-1}$	0.1536**	0.0928*					0.0482**	0.0314*	0.1119**	0.0924**	0.031*	0.0183.
	(0.0478)	(0.0391)					(0.0167)	(0.0136)	(0.0376)	(0.0322)	(0.013)	(0.0109)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0126*	-0.0081	0.1054***	0.1043***			0.0975***	0.0868***	-0.0133*	-0.0088
			(0.006)	(0.006)	(0.02)	(0.0189)			(0.0207)	(0.0195)	(0.0066)	(0.0063)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0044	0.006	-0.0394.	-0.007			-0.0429*	-0.0178	0.002	0.0068
			(0.0058)	(0.005)	(0.0228)	(0.0192)			(0.02)	(0.0181)	(0.0053)	(0.0048)
$Spill(A)^{\tau,up}_{i,t-1}$	2.435***	2.572***					0.7004**	0.3476*	2.363***	2.642***	0.4757**	0.2599.
	(0.7017)	(0.5889)					(0.2131)	(0.1672)	(0.6273)	(0.5391)	(0.156)	(0.1388)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0606	-0.0573					-0.0539***	-0.0369**	-0.0695.	-0.059.	-0.0514***	-0.0378**
	(0.0417)	(0.035)					(0.016)	(0.013)	(0.0369)	(0.0337)	(0.0144)	(0.0126)
$W_{i,t-1}$		-0.0173		-0.0047.		-0.0276**		-0.0056		-0.0333**		-0.0036
		(0.0139)		(0.0028)		(0.0104)		(0.0042)		(0.0121)		(0.0034)
$(K/L)_{i,t-1}$		0.0238		-4e-04		0.0207		-0.0065		0.0152		-0.0029
		(0.0157)		(0.0034)		(0.0132)		(0.0044)		(0.0145)		(0.0037)
$(L^P/L)_{i,t-1}$		0.2489.		-0.0135		0.1575		-0.0215		0.1662		-0.0247
		(0.1279)		(0.0323)		(0.1089)		(0.0424)		(0.1241)		(0.0341)
$(I/L)_{i,t-1}$		0.0289*		0.0118***		0.0315**		0.0108***		0.0216.		0.0107***
		(0.0114)		(0.0029)		(0.0104)		(0.0032)		(0.0112)		(0.0029)
$(E/L)_{i,t-1}$		-0.0032		-0.0084**		8e-04		-0.0116**		0.0048		-0.0086**
		(0.0143)		(0.003)		(0.0122)		(0.0037)		(0.013)		(0.003)
$(M/L)_{i,t-1}$		0.0011		-9e-04		0.0024		0.0049		0.014		4e-04
		(0.0161)		(0.0037)		(0.0127)		(0.005)		(0.0134)		(0.0036)
$(W^P/W)_{i,t-1}$		-0.2207.		-0.0413		-0.2831**		0.0278		-0.2376*		0.011
		(0.1287)		(0.0251)		(0.1071)		(0.0252)		(0.116)		(0.0226)
AR(1)	0	0	1e-04	2e-04	0	0	7e-04	5e-04	0	0	5e-04	7e-04
AR(2)	0.9373	0.9079	0.899	0.8057	0.9237	0.9583	0.6394	0.7465	0.9656	0.978	0.7307	0.7026
Sargan	0	0	0	0.001	0	0	0	0	0	1e-04	0	0.0056
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9284	0.9354	0.996	0.9962	0.9363	0.9402	0.9952	0.9958	0.9332	0.9374	0.9957	0.996

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009).

Table C.4: Demand-pull and technology-push effects — Arellano-Bond estimator.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.3431***	0.306***	0.0108	0.0314	0.8299***	0.6401***			0.5894***	0.5672***	0.0391	0.0401
	(0.082)	(0.0596)	(0.0243)	(0.0218)	(0.0918)	(0.0795)			(0.1084)	(0.0832)	(0.0261)	(0.027)
$A^{\tau}_{i,t-1}$	-0.2727	-0.2537	0.8206***	0.6053***			0.7537***	0.3797**	-0.3969	-0.1191	0.7526***	0.3715**
	(0.4007)	(0.304)	(0.0567)	(0.0755)			(0.1279)	(0.1365)	(0.527)	(0.3246)	(0.126)	(0.1255)
$PR^{\mu,up}_{i,t-1}$			-0.0015	-0.0018	-0.0686*	-0.055.			-0.0806**	-0.0682*	-0.0081	-0.0094
			(0.0052)	(0.0051)	(0.0304)	(0.0322)			(0.0308)	(0.0278)	(0.0056)	(0.0057)
$PR^{\mu,dw}_{i,t-1}$			-6e-04	-7e-04	-0.0916**	-0.0607*			-0.0762**	-0.052*	-0.0036	-0.0019
			(0.0052)	(0.0044)	(0.0295)	(0.0289)			(0.0281)	(0.0244)	(0.005)	(0.0042)
$PR^{\tau,dw}_{i,t-1}$	0.5732*	0.377*					0.0285	0.0095	0.7663**	0.4663**	-0.02	-0.0046
	(0.2659)	(0.173)					(0.045)	(0.0432)	(0.2921)	(0.1773)	(0.0419)	(0.0427)
$Spill(A)^{\mu,up}_{i,t-1}$			0.0017	2e-04	-0.059	-0.0373			-0.0132	-0.0207	0.0074	0.0032
			(0.0086)	(0.008)	(0.0486)	(0.0457)			(0.0522)	(0.0411)	(0.009)	(0.0096)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0064	0.0025	-0.2074***	-0.1591***			-0.1184**	-0.12**	0.0099	0.0115
			(0.0057)	(0.006)	(0.0402)	(0.0367)			(0.0452)	(0.0405)	(0.0061)	(0.0071)
$Spill(A)^{\tau,up}_{i,t-1}$	10.37**	6.151**					1.853***	1.598***	11.62***	8.457***	1.517***	1.322***
	(3.25)	(2.199)					(0.4343)	(0.4336)	(2.676)	(1.961)	(0.355)	(0.3967)
$Spill(A)^{\tau,dw}_{i,t-1}$	0.2045	0.0152					-0.0145	0.0341	0.1705	0.0418	0.0013	0.0329
	(0.1595)	(0.1065)					(0.0326)	(0.0326)	(0.1544)	(0.1052)	(0.0327)	(0.0317)
$W_{i,t-1}$		0.112*		-0.0202.		0.1671**		0.0024		0.1328**		1e-04
		(0.0568)		(0.0114)		(0.0567)		(0.0163)		(0.0471)		(0.0155)
$(K/L)_{i,t-1}$		-0.0374		0.02		0.0069		0.0317.		-0.0112		0.0384*
		(0.0767)		(0.0153)		(0.0717)		(0.0186)		(0.0763)		(0.0175)
$(L^P/L)_{i,t-1}$		-0.7078		0.2495.		-0.3813		0.1315		-0.0839		0.2425
		(0.666)		(0.1496)		(0.5939)		(0.1788)		(0.6121)		(0.1692)
$(I/L)_{i,t-1}$		0.044		0.0055		0.0387		0.0053		0.0558.		0.0015
		(0.04)		(0.0061)		(0.0338)		(0.0073)		(0.0326)		(0.0068)
$(E/L)_{i,t-1}$		-0.1974***		-0.028**		-0.2233***		-0.0383**		-0.1512**		-0.0376**
		(0.0536)		(0.0106)		(0.0476)		(0.014)		(0.0471)		(0.0122)
$(M/L)_{i,t-1}$		0.0141		0.0321*		-0.0345		0.0185		-0.0803		0.0201
		(0.0746)		(0.0137)		(0.064)		(0.0201)		(0.0665)		(0.0172)
$(W^P/W)_{i,t-1}$		0.0194		-0.0642		-0.247		-0.0824		-0.2412		-0.0821
		(0.2929)		(0.0584)		(0.2868)		(0.0626)		(0.2703)		(0.0632)
AR(1)	0	0	2e-04	4e-04	0	0	3e-04	0.0136	0	0	5e-04	0.0125
AR(2)	0.4028	0.3798	0.7767	0.5895	0.8789	0.8175	0.5217	0.3777	0.4567	0.523	0.5125	0.3298
Sargan	1e-04	0	0	3e-04	0	0	0	1e-04	4e-04	6e-04	0	1e-04
Controls		Y		Y		Y		Y		Y		Y
R^2	0.0034	0.0137	0.6304	0.6608	0.0027	0.0027	0.6421	0.6892	0.0054	0.0151	0.6462	0.6883

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Arellano-Bond (AB) first-difference model. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1.

Table C.5: Demand-pull and technology-push effects — weighted FE model

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.3838***	0.3538***	0.0111.	0.0046	0.4142***	0.3616***			0.3997***	0.3601***	0.0128*	0.0048
	(0.0213)	(0.0223)	(0.0061)	(0.0065)	(0.0259)	(0.0275)			(0.0259)	(0.0273)	(0.006)	(0.0064)
$A^{\tau}_{i,t-1}$	0.2423***	0.1392.	0.7802***	0.7295***			0.8407***	0.7835***	0.2542***	0.1491*	0.8375***	0.7838***
	(0.0718)	(0.0753)	(0.0134)	(0.0152)			(0.0202)	(0.0212)	(0.0712)	(0.0745)	(0.0202)	(0.0212)
$PR^{\mu,up}_{i,t-1}$			-0.0019	-0.0015	0.0228**	0.0277***			0.0221**	0.0267**	-0.0022	-0.0017
			(0.0021)	(0.0021)	(0.0084)	(0.0084)			(0.0083)	(0.0083)	(0.0021)	(0.0021)
$PR^{\mu,dw}_{i,t-1}$			-0.0019	-0.0014	0.0326***	0.0393***			0.0314***	0.0375***	-0.0019	-0.0013
			(0.0017)	(0.0017)	(0.007)	(0.007)			(0.0069)	(0.007)	(0.0017)	(0.0017)
$PR^{\tau,dw}_{i,t-1}$	0.0775*	0.0541.					-0.0094	-0.0159*	0.0727*	0.0514	-0.0124.	-0.0177*
	(0.0316)	(0.0328)					(0.0074)	(0.0075)	(0.0314)	(0.0326)	(0.0074)	(0.0076)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0061	-0.0058	8e-04	-0.0016			0.0107	0.0048	-0.0052	-0.0053
			(0.0042)	(0.0041)	(0.0169)	(0.0167)			(0.0169)	(0.0168)	(0.0042)	(0.0041)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0024	0.0026	-0.0278**	-0.0242*			-0.0275**	-0.0259*	0.0021	0.0027
			(0.0026)	(0.0026)	(0.0106)	(0.0106)			(0.0106)	(0.0106)	(0.0025)	(0.0025)
$Spill(A)^{\tau,up}_{i,t-1}$	1.268***	1.216***					0.4938***	0.509***	1.343***	1.268***	0.4822***	0.4925***
	(0.3483)	(0.349)					(0.0924)	(0.0924)	(0.3466)	(0.3461)	(0.0928)	(0.0928)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0915**	-0.0824**					-0.0222**	-0.0146.	-0.0887**	-0.0766**	-0.021**	-0.0143.
	(0.0288)	(0.0289)					(0.0077)	(0.0077)	(0.0286)	(0.0286)	(0.0077)	(0.0077)
$W_{i,t-1}$		0.0246*		-0.0014		0.0237*		9e-04		0.025*		6e-04
		(0.0102)		(0.0024)		(0.0102)		(0.0023)		(0.0103)		(0.0024)
$(K/L)_{i,t-1}$		0.0033		0.0042		0.0053		0.005.		2e-04		0.0049
		(0.0127)		(0.003)		(0.0123)		(0.003)		(0.0126)		(0.003)
$(L^P/L)_{i,t-1}$		-0.0915		0.0142		-0.1232		0.0174		-0.0646		0.0166
		(0.1251)		(0.0292)		(0.1231)		(0.0291)		(0.1237)		(0.0291)
$(I/L)_{i,t-1}$		0.0174*		0.0057**		0.0149.		0.006**		0.0174*		0.0059**
		(0.0088)		(0.0021)		(0.0087)		(0.0021)		(0.0087)		(0.0021)
$(E/L)_{i,t-1}$		-0.0672***		-0.0151***		-0.0782***		-0.0149***		-0.0733***		-0.0143***
		(0.0113)		(0.0027)		(0.0111)		(0.0027)		(0.0112)		(0.0027)
$(M/L)_{i,t-1}$		0.0223.		0.0101***		0.0325**		0.0087**		0.0257*		0.0084**
		(0.0123)		(0.0029)		(0.012)		(0.0029)		(0.0122)		(0.0029)
$(W^P/W)_{i,t-1}$		-0.0021		-0.0431*		0.0035		-0.041*		0.0135		-0.0417*
		(0.0766)		(0.0182)		(0.076)		(0.018)		(0.0757)		(0.018)
Controls		Y		Y		Y		Y		Y		Y
R^2	0.8118	0.8175	0.9955	0.9957	0.8114	0.8197	0.9956	0.9958	0.816	0.8224	0.9956	0.9958

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways weighted fixed-effects (FE) model. The weights used in the regressions are $A^{\mu}_{i,t}$ in the TFP regression and $L_{i,t}$ in all other regressions. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^P_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1.

Table C.6: Demand-pull and technology-push effects — first subperiod.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5807***	0.5313***	0.0252	0	0.5993***	0.4622***			0.5934***	0.4794***	0.0281	0.0035
	(0.0854)	(0.0946)	(0.0208)	(0.0196)	(0.098)	(0.0932)			(0.0854)	(0.0926)	(0.0206)	(0.0202)
$A^{\tau}_{i,t-1}$	-0.0539	-0.0557	1.092***	1.045***			0.9694***	0.9981***	0.0116	0.0648	1.027***	1.027***
	(0.1777)	(0.1536)	(0.0218)	(0.02)			(0.1289)	(0.0688)	(0.1535)	(0.1416)	(0.0844)	(0.056)
$PR^{\mu,up}_{i,t-1}$			-0.0128	-0.0047	0.0072	-0.0051			0.0091	-0.013	-0.0197	-0.0068
			(0.0127)	(0.0075)	(0.0309)	(0.029)			(0.0314)	(0.0294)	(0.0159)	(0.0085)
$PR^{\mu,dw}_{i,t-1}$			-0.0035	0.0018	0.0492	-0.0506			0.0037	-0.05	-0.0052	9e-04
			(0.0117)	(0.0077)	(0.0384)	(0.0363)			(0.0368)	(0.0352)	(0.0135)	(0.008)
$PR^{\tau,dw}_{i,t-1}$	0.1011	0.0809					0.1253	0.0574	0.0759	0.0421	0.06	0.0267
	(0.0932)	(0.0742)					(0.0872)	(0.0373)	(0.0651)	(0.0595)	(0.0459)	(0.0255)
$Spill(A)^{\mu,up}_{i,t-1}$			0.0022	0.0028	0.0757	-0.0686			0.0173	-0.092	-0.0038	-0.0136
			(0.0369)	(0.0262)	(0.0984)	(0.086)			(0.0998)	(0.0913)	(0.0381)	(0.0285)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0036	0.003	0.0481	0.0641			0.0242	0.0569	5e-04	0
			(0.0156)	(0.0104)	(0.0427)	(0.044)			(0.0418)	(0.0462)	(0.0139)	(0.0111)
$Spill(A)^{\tau,up}_{i,t-1}$	1.827	2.831*					-0.2011	-0.6991	1.827.	2.389*	-0.4824	-0.6271*
	(1.163)	(1.165)					(0.5279)	(0.4404)	(1.029)	(1.015)	(0.348)	(0.2954)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0337	-0.0037					-0.0314	-0.0066	-0.0539	-0.049	-0.0194	-0.0054
	(0.0679)	(0.0695)					(0.0308)	(0.0236)	(0.0641)	(0.0676)	(0.0251)	(0.0212)
$W_{i,t-1}$		-0.0192		-0.011*		-0.004		-0.0085		-0.0136		-0.0053
		(0.0211)		(0.0049)		(0.019)		(0.0069)		(0.02)		(0.0059)
$(K/L)_{i,t-1}$		0.0791.		0.0074		0.0611		0.0164		0.0553		0.0082
		(0.0473)		(0.009)		(0.038)		(0.014)		(0.0377)		(0.0099)
$(L^P/L)_{i,t-1}$		0.535.		-0.0097		0.0544		0.0562		0.0925		0.0252
		(0.315)		(0.0721)		(0.2134)		(0.0893)		(0.2318)		(0.0676)
$(I/L)_{i,t-1}$		0.0493*		0.0084.		0.0422*		0.0066		0.0375*		0.0075
		(0.0204)		(0.0044)		(0.0173)		(0.0071)		(0.0178)		(0.0057)
$(E/L)_{i,t-1}$		-3e-04		-0.0055		-0.027		-0.028*		-0.0276		-0.0075
		(0.035)		(0.0062)		(0.0238)		(0.0111)		(0.0242)		(0.0075)
$(M/L)_{i,t-1}$		-0.0498		0.0023		1e-04		0.0133		0.0062		8e-04
		(0.0403)		(0.0074)		(0.026)		(0.0122)		(0.0279)		(0.0075)
$(W^P/W)_{i,t-1}$		-0.4005		-0.1213*		-0.3473		-0.1095		-0.1988		-0.1154.
		(0.2947)		(0.0557)		(0.2158)		(0.0834)		(0.2344)		(0.0605)
AR(1)	0	0	0.0378	0.0384	0	2e-04	0.0227	0.0477	0	1e-04	0.0479	0.0534
AR(2)	0.5155	0.6397	0.8436	0.8225	0.5133	0.4159	0.8396	0.8501	0.5298	0.4975	0.8122	0.818
Sargan	0.0232	2e-04	0.0011	4e-04	1e-04	1e-04	0	3e-04	9e-04	0.0063	1e-04	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9435	0.9398	0.995	0.9958	0.9476	0.949	0.9908	0.9942	0.9466	0.9467	0.9944	0.9954

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009).

Table C.7: Demand-pull and technology-push effects — second subperiod

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.4469***	0.4156***	-0.006	-9e-04	0.522***	0.5089***			0.5242***	0.5032***	-0.0074	-0.0026
	(0.0409)	(0.0323)	(0.0213)	(0.0201)	(0.0459)	(0.0519)			(0.0514)	(0.049)	(0.0236)	(0.0193)
$A^{\tau}_{i,t-1}$	-0.1027	0.057	1.022***	1.007***			1.053***	1.077***	-0.001	0.0045	1.084***	1.07***
	(0.1537)	(0.1308)	(0.0111)	(0.0124)			(0.0536)	(0.0482)	(0.1241)	(0.1255)	(0.0468)	(0.0388)
$PR^{\mu,up}_{i,t-1}$			-0.0014	-8e-04	0.0076	0.0183			0.0115	0.0135	0.0014	-0.0011
			(0.0057)	(0.0059)	(0.0162)	(0.0135)			(0.0171)	(0.0142)	(0.0058)	(0.0056)
$PR^{\mu,dw}_{i,t-1}$			0.0017	0.004	-0.0045	0.0034			0.0026	0.0033	0.004	0.0036
			(0.004)	(0.004)	(0.016)	(0.0133)			(0.0164)	(0.0134)	(0.0041)	(0.0037)
$PR^{\tau,dw}_{i,t-1}$	0.3035***	0.1018.					0.0681*	0.0098	0.2048***	0.1362**	0.0293	0.0047
	(0.0835)	(0.0567)					(0.0272)	(0.0169)	(0.0563)	(0.05)	(0.0195)	(0.014)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0118*	-0.0085	0.1106***	0.0956***			0.0989***	0.0831***	-0.0148*	-0.0101
			(0.006)	(0.0062)	(0.0216)	(0.0217)			(0.0225)	(0.0209)	(0.0067)	(0.0065)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0015	0.0058	-0.0266	-0.0373			-0.0342	-0.0442.	-0.0029	0.0032
			(0.0066)	(0.0061)	(0.0247)	(0.0245)			(0.0237)	(0.0227)	(0.0063)	(0.0058)
$Spill(A)^{\tau,up}_{i,t-1}$	3.601**	2.055*					1.973***	1.071***	2.738**	2.793***	1.366***	0.9312***
	(1.185)	(0.8783)					(0.3517)	(0.2817)	(0.882)	(0.8156)	(0.299)	(0.2517)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.1629.	-0.1361*					-0.0883***	-0.0581**	-0.1768**	-0.1412*	-0.0737***	-0.0517***
	(0.0874)	(0.0579)					(0.0255)	(0.0181)	(0.0636)	(0.0572)	(0.019)	(0.0151)
$W_{i,t-1}$		-0.0125		-0.0013		-0.0389.		-0.0012		-0.0382*		-0.0027
		(0.0261)		(0.0051)		(0.0214)		(0.0082)		(0.0191)		(0.0056)
$(K/L)_{i,t-1}$		0.0077		9e-04		-0.0078		-0.0038		-0.0139		-0.0015
		(0.0246)		(0.005)		(0.0203)		(0.0066)		(0.0217)		(0.0054)
$(L^P/L)_{i,t-1}$		0.3218		0.0316		0.385		-0.0255		0.2817		-0.0374
		(0.2343)		(0.0499)		(0.2443)		(0.0715)		(0.2319)		(0.0523)
$(I/L)_{i,t-1}$		0.0249		0.0099*		0.0177		0.0089.		0.0162		0.01*
		(0.0193)		(0.0048)		(0.0225)		(0.0046)		(0.0195)		(0.0045)
$(E/L)_{i,t-1}$		0.0293		-0.0121**		0.0456*		-0.0067		0.0472*		-0.0089.
		(0.0211)		(0.0044)		(0.023)		(0.0062)		(0.0195)		(0.0048)
$(M/L)_{i,t-1}$		0.0011		0.001		0.0178		0.003		0.0216		0.0032
		(0.0276)		(0.0052)		(0.0211)		(0.0076)		(0.0213)		(0.0049)
$(W^P/W)_{i,t-1}$		-0.4345*		-0.0334		-0.7856***		0.0127		-0.5908**		0.0176
		(0.1802)		(0.0409)		(0.2207)		(0.0399)		(0.1873)		(0.0341)
AR(1)	1e-04	1e-04	2e-04	3e-04	0	0	1e-04	0.0016	0	0	0.001	0.0019
AR(2)	0.5792	0.3485	0.3267	0.2549	0.4284	0.2814	0.301	0.176	0.5271	0.4214	0.2331	0.1869
Sargan	0	0	0	0	0	0	0.0234	4e-04	0	0	5e-04	4e-04
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9009	0.929	0.9964	0.9964	0.9308	0.9316	0.9943	0.9963	0.9184	0.9275	0.9958	0.9964

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009).

C.2. The direction of technological change

This section provides a sample of additional results and robustness checks about the impact of TP and DP on the direction of technological change. Table C.8 shows the same results as discussed in Sec. 5.2.2 including industry level controls and autoregressive terms.

Table C.9 and C.10 the regression results from models relying on alternative estimators (one-step System-GMM à la Blundell and Bond (1998) and two-step difference GMM à la Arellano and Bond (1991)). Both control for two-ways FE, i.e. include time and industry dummies. As the test statistics suggest, these models severely suffer from weak instruments. Additional tests, which are not presented here, suggest that these estimation difficulties can not be resolved if instruments are collapsed or deeper lags are used as instruments.

Notably, the performance of these models is much better if different subperiods or subgroups of industries are considered suggesting non-trivial patterns over time and industries, which are hard to identify in these linear models. However, a deeper search for suitable identification strategies is beyond the scope of this paper.

Lastly, the results for the two subperiods are provided in C.11 and C.12.

Table C.8: Productivity, labor, capital, and production labor

	Productivity				Labor & Wages				Capital & Investment				Production labor			
	$TFP_{i,t}$	$TFP_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$L_{i,t}$	$L_{i,t}$	$W_{i,t}$	$W_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$A^{\mu}_{i,t-1}$	0.0459**	0.0275.	-0.1465*	-0.1469*	-0.2349***	-0.0895*	-0.2227***	-0.2082***	0.1234***	0.0492*	-0.1769*	-0.1578.	-0.0099*	-0.0149***	-0.0138.	-0.0186*
	(0.0166)	(0.0159)	(0.0624)	(0.0629)	(0.0426)	(0.0438)	(0.0526)	(0.0527)	(0.0216)	(0.0213)	(0.0886)	(0.0923)	(0.0041)	(0.0043)	(0.0072)	(0.0075)
$A^{\tau}_{i,t-1}$	0.0966*	0.0096	-0.1031	-0.0482	-0.4202***	-0.019	-0.0747	-0.0632	0.2042***	0.0924	-0.598*	-0.1016	-0.038***	-0.0265*	-0.0669***	-0.0306
	(0.0452)	(0.0446)	(0.1587)	(0.1675)	(0.1152)	(0.1171)	(0.1337)	(0.1402)	(0.0587)	(0.0568)	(0.237)	(0.2458)	(0.0112)	(0.0115)	(0.0195)	(0.0201)
$PR^{\mu,up}_{i,t-1}$	0.0034	0.0082.	0.042*	0.047*	0.0258.	0.0223.	0.0585***	0.0596***	-0.0017	-0.0048	0.0577.	0.0602*	0.0013	0.0013	0.0068**	0.0069**
	(0.0051)	(0.0048)	(0.0196)	(0.0196)	(0.0142)	(0.0136)	(0.0166)	(0.0164)	(0.0072)	(0.0067)	(0.0294)	(0.0288)	(0.0014)	(0.0013)	(0.0024)	(0.0024)
$PR^{\mu,dw}_{i,t-1}$	0.0063	0.0123**	0.046**	0.057***	0.024*	0.0265*	0.0371**	0.0398**	-0.0027	-0.0096.	0.0629**	0.0619**	-7e-04	-1e-04	-3e-04	0
	(0.0043)	(0.0041)	(0.0162)	(0.0163)	(0.0117)	(0.0112)	(0.0136)	(0.0136)	(0.0059)	(0.0055)	(0.0242)	(0.0239)	(0.0011)	(0.0011)	(0.002)	(0.0019)
$PR^{\tau,dw}_{i,t-1}$	-0.0041	-0.0166	-0.1013	-0.0463	-0.155**	0.0136	0.0284	0.0841	0.1312***	0.0384	0.1126	0.1945.	-0.0026	-0.0064	0.0248**	0.0265**
	(0.0196)	(0.0192)	(0.0734)	(0.0745)	(0.052)	(0.0514)	(0.0619)	(0.0623)	(0.0262)	(0.0252)	(0.1078)	(0.1093)	(0.005)	(0.0051)	(0.0087)	(0.0089)
$Spill(A)^{\mu,up}_{i,t-1}$	-0.0111	-0.0117	-0.0742.	-0.0815*	-0.0743*	-0.0555.	-0.0718*	-0.0672.	0.0424**	0.0319*	-0.0883	-0.1051.	-9e-04	-0.0025	0.0107*	0.0088.
	(0.0103)	(0.0097)	(0.0412)	(0.0411)	(0.0297)	(0.0284)	(0.0348)	(0.0344)	(0.0151)	(0.0139)	(0.0615)	(0.0604)	(0.0029)	(0.0028)	(0.005)	(0.0049)
$Spill(A)^{\mu,dw}_{i,t-1}$	-0.016*	-0.0135*	-0.0161	-0.0176	0.0032	-0.0079	-0.004	-0.0085	-0.0046	-0.0035	-0.0041	-0.0165	-2e-04	7e-04	0.0032	0.0033
	(0.0065)	(0.0062)	(0.0252)	(0.0252)	(0.0181)	(0.0175)	(0.0212)	(0.0212)	(0.0092)	(0.0086)	(0.0376)	(0.0371)	(0.0018)	(0.0017)	(0.0031)	(0.003)
$Spill(A)^{\tau,up}_{i,t-1}$	-0.7711***	-0.7479***	-1.471.	-1.207	-0.754	-0.4783	-1.533*	-1.336*	0.1511	0.0448	0.3971	1.124	-0.2311***	-0.201***	-0.3043**	-0.2156*
	(0.2122)	(0.2002)	(0.7862)	(0.7875)	(0.5666)	(0.5451)	(0.6627)	(0.661)	(0.288)	(0.2676)	(1.174)	(1.159)	(0.0551)	(0.0543)	(0.0961)	(0.0946)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0424*	-0.0225	0.0341	0.0382	0.0839.	0.0322	0.0474	0.0451	-0.0202	-0.0286	0.2051*	0.1815.	0.0043	0.0043	-0.0014	-0.0041
	(0.0176)	(0.0167)	(0.0659)	(0.066)	(0.0478)	(0.0459)	(0.0556)	(0.0554)	(0.0242)	(0.0224)	(0.0988)	(0.0971)	(0.0046)	(0.0045)	(0.0081)	(0.0079)
$TFP_{i,t-1}$	0.9444***	0.8321***														
	(0.0162)	(0.0246)														
$(VA/L)_{i,t-1}$			0.8153***	0.6924***												
			(0.0143)	(0.0426)												
$L_{i,t-1}$					0.8415***	0.96***										
					(0.0145)	(0.0275)										
$W_{i,t-1}$		0.0579***		0.1659***		-0.0373*	0.8332***	0.8407***		0.013		0.0688.		0.0052**		0.0119***
		(0.0091)		(0.048)		(0.0174)	(0.0129)	(0.0201)		(0.0081)		(0.0353)		(0.0017)		(0.0029)
$(K/L)_{i,t-1}$		0.0363***		-0.0544.		-0.111***		-0.0604*	0.8275***	-0.0434***		-0.2473***		0.0048*		-0.0146***
		(0.0077)		(0.0297)		(0.0209)		(0.0249)	(0.016)	(0.0128)		(0.0437)		(0.002)		(0.0036)
$(I/L)_{i,t-1}$		-0.0473***		0.0411.		0.0605***		0.0718***		0.0808***	0.5464***	0.4823***		-0.005***		-3e-04
		(0.005)		(0.0212)		(0.0151)		(0.0176)		(0.0074)	(0.0208)	(0.0308)		(0.0014)		(0.0025)
$(L^P/L)_{i,t-1}$		0.1587*		1.114***		1.336***		1.127***		-0.7374***		1.161**	0.6768***	0.6286***		0.182***
		(0.0735)		(0.304)		(0.209)		(0.253)		(0.1028)		(0.4435)	(0.0193)	(0.0208)		(0.0362)
$(W^P/W)_{i,t-1}$		0.0349		-0.2356		-0.4672***		-0.3293*		0.2112***		-0.379		0.0909***	0.5492***	0.4784***
		(0.0446)		(0.1882)		(0.1296)		(0.1571)		(0.0638)		(0.2753)		(0.0129)	(0.0216)	(0.0225)
$(E/L)_{i,t-1}$		-0.048***		-0.0856**		-0.0476*		-0.0861***		-0.0147		0.2205***		0.0039*		0.011***
		(0.007)		(0.0274)		(0.022)		(0.0228)		(0.0096)		(0.0399)		(0.0019)		(0.0033)
$(M/L)_{i,t-1}$		-0.0012		0.0118		-0.0769***		0.0225		0.0297**		0.0139		-0.0062**		-0.0043
		(0.0073)		(0.0294)		(0.0206)		(0.0247)		(0.0102)		(0.0432)		(0.002)		(0.0035)
Controls		Y		Y		Y		Y		Y		Y		Y		Y
R^2	0.7438	0.7746	0.9007	0.9024	0.929	0.9359	0.9251	0.927	0.9135	0.927	0.8259	0.8339	0.8778	0.8832	0.662	0.6776

Notes: The table shows the regression results of productivity, labor demand, capital use, and production labor on demand-pull and technology-push effects. The estimation is based on a two-ways weighted fixed-effects (FE) model. The weights used in the regressions are $A^{\mu}_{i,t}$ in the TFP regression and $L_{i,t}$ in all other regressions. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1.

Table C.9: Productivity, labor, capital, and production labor — Blundell-Bond estimator.

	Productivity				Labor & Wages				Capital & Investment				Production labor			
	$TFP_{i,t}$	$TFP_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$L_{i,t}$	$L_{i,t}$	$W_{i,t}$	$W_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$A^{\mu}_{i,t-1}$	-0.0033	0.0358	-0.359*	-0.0498	0.0606	0.2302*	-0.2898*	-0.0156	0.0782.	0.0113	-0.1454	0.0202	0	1e-04	-0.0171	-0.0121
	(0.0269)	(0.0256)	(0.1435)	(0.1334)	(0.0875)	(0.0914)	(0.1267)	(0.1125)	(0.0453)	(0.0401)	(0.163)	(0.1756)	(0.0087)	(0.0077)	(0.0147)	(0.0135)
$A^{\tau}_{i,t-1}$	-0.0456	-0.0725	-0.4094	-0.929***	-0.3931**	-0.5861***	-0.5227*	-0.6681***	0.1251	0.1459*	-0.4306	-0.4793	-0.0441**	-0.0392*	-5e-04	0.0197
	(0.0737)	(0.0535)	(0.254)	(0.2354)	(0.1456)	(0.1568)	(0.2376)	(0.1951)	(0.0848)	(0.0689)	(0.2926)	(0.2939)	(0.0154)	(0.0161)	(0.0283)	(0.0243)
$PR^{\mu,up}_{i,t-1}$	0.034***	0.0199*	0.1175**	0.078.	-0.0312	-0.0077	0.0369	0.0529	0.0066	0.0043	0.001	0.0178	0.0029	0.0024	0.0098.	0.0106*
	(0.0093)	(0.009)	(0.0416)	(0.0401)	(0.0249)	(0.026)	(0.0369)	(0.0383)	(0.0169)	(0.0139)	(0.0571)	(0.0545)	(0.0023)	(0.0022)	(0.005)	(0.0047)
$PR^{\mu,dw}_{i,t-1}$	0.0299***	0.0287***	0.1951***	0.1946***	0.0679***	0.0969***	0.1466***	0.1326***	-0.0291*	-0.0476***	0.1526***	0.1777***	7e-04	0.0013	0.0039	0.0039
	(0.0086)	(0.0085)	(0.0402)	(0.039)	(0.0198)	(0.0202)	(0.0308)	(0.0291)	(0.0128)	(0.0124)	(0.0405)	(0.0396)	(0.0022)	(0.0023)	(0.0045)	(0.0041)
$PR^{\tau,dw}_{i,t-1}$	0.1629***	0.1313***	0.5601***	0.4807***	-0.0242	0.0193	0.645***	0.3945***	0.0887*	-0.0065	0.2954*	0.208	0.0033	0.0088	-0.0179.	-0.0195.
	(0.0461)	(0.0394)	(0.1325)	(0.0957)	(0.0685)	(0.0575)	(0.1311)	(0.0808)	(0.0367)	(0.0257)	(0.126)	(0.1343)	(0.0064)	(0.0058)	(0.0108)	(0.0102)
$Spill(A)^{\mu,up}_{i,t-1}$	-8e-04	-0.0068	-0.0355	-0.0593	-0.0652	-0.0675	-0.1059.	-0.0435	0.03	0.0551*	-0.1245.	-0.1086	-0.0014	-0.0019	0.0019	-0.005
	(0.016)	(0.0141)	(0.069)	(0.0645)	(0.0489)	(0.0481)	(0.0589)	(0.0577)	(0.0277)	(0.0271)	(0.0748)	(0.0782)	(0.0041)	(0.004)	(0.0078)	(0.0071)
$Spill(A)^{\mu,dw}_{i,t-1}$	-0.0121	-0.0068	0.0973.	0.065	0.0698*	0.0513	0.1128**	0.0667.	-0.0311.	-0.0225	0.1198.	0.1246.	-0.0021	-0.0018	0.0037	-0.0053
	(0.0108)	(0.0108)	(0.0513)	(0.0512)	(0.0329)	(0.0321)	(0.0433)	(0.0397)	(0.0184)	(0.0163)	(0.0715)	(0.0671)	(0.0034)	(0.0031)	(0.0068)	(0.0062)
$Spill(A)^{\tau,up}_{i,t-1}$	-0.6915	-0.4913	-3.865.	-2.116	-2.37.	-2.604*	-2.985	-0.6153	0.2543	0.8965	-2.12	-4.18.	-0.0994	-0.0988	-0.2208	-0.1931
	(0.5408)	(0.445)	(2.161)	(2.084)	(1.304)	(1.231)	(1.905)	(1.591)	(0.6839)	(0.5913)	(2.159)	(2.158)	(0.093)	(0.0823)	(0.158)	(0.1577)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0858*	-0.0471	-0.0865	0.2426*	0.2694***	0.3773***	-0.059	0.1556.	-0.1474***	-0.1257***	0.1224	0.2247	0.0226***	0.0175*	0.0105	0.0049
	(0.0363)	(0.0331)	(0.1115)	(0.1058)	(0.0727)	(0.0768)	(0.1019)	(0.0873)	(0.0418)	(0.0337)	(0.1416)	(0.1427)	(0.0064)	(0.0071)	(0.0129)	(0.0122)
AR(1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR(2)	0.0165	0.0222	0.0032	6e-04	3e-04	0	0.0461	0.0332	9e-04	0.0025	0.1265	0.0301	0.6521	0.5527	0.5203	0.3256
Sargan	0	0.0059	0	0.0035	0	0.0024	0	5e-04	1e-04	9e-04	0.0025	6e-04	0	0.0015	0.083	0.0182
Controls		Y		Y		Y		Y		Y		Y		Y		Y
R^2	0.9554	0.9625	0.9934	0.994	0.9877	0.9872	0.9929	0.9943	0.9466	0.953	0.9718	0.9724	0.9942	0.9944	0.993	0.9933

Notes: The table shows the regression results of productivity, labor demand, capital use, and production labor on demand-pull and technology-push effects. The estimation is based on a oneways Blundell-Bond (BB) system GMM model. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009).

Table C.10: Productivity, labor, capital, and production labor — Arellano-Bond estimator.

	Productivity				Labor & Wages				Capital & Investment				Production labor			
	$TFP_{i,t}$	$TFP_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$L_{i,t}$	$L_{i,t}$	$W_{i,t}$	$W_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$A^{\mu}_{i,t-1}$	0.0311	-0.005	-0.1821	-0.2775	0.108	-0.0092	0.0303	-0.1197	0.1205	-0.0255	0.3788	0.5065	-0.0213	-0.028.	-0.0179	-0.0567**
	(0.0474)	(0.0429)	(0.2127)	(0.2087)	(0.1802)	(0.1727)	(0.1913)	(0.2038)	(0.1109)	(0.0824)	(0.2382)	(0.353)	(0.015)	(0.0146)	(0.0252)	(0.0198)
$A^{\tau}_{i,t-1}$	0.0193	-0.0353	-0.8719	-0.7764	-1.201*	-0.8362.	-0.7636	-0.3618	0.1326	-0.0756	0.5511	0.6003	-0.0741.	-0.082	-0.1396*	-0.0846
	(0.2145)	(0.1451)	(0.7167)	(0.6369)	(0.466)	(0.4727)	(0.5821)	(0.5691)	(0.272)	(0.2861)	(0.9901)	(1.265)	(0.0437)	(0.0505)	(0.0692)	(0.0598)
$PR^{\mu,up}_{i,t-1}$	0.0064	0.0046	0.0374	0.0287	0.0292	0.0077	0.0246	0.0441	-0.0157	-0.0148	-0.0469	-0.0235	0.0076*	0.0039	0.0105*	0.0125*
	(0.0117)	(0.0129)	(0.0526)	(0.0526)	(0.0447)	(0.0443)	(0.0493)	(0.0626)	(0.0204)	(0.0173)	(0.0766)	(0.0947)	(0.0035)	(0.0037)	(0.0049)	(0.0054)
$PR^{\mu,dw}_{i,t-1}$	0.0084	0.0172	0.0707	0.0395	0.0802*	0.0534	0.0482	0.0922*	-0.021	-0.0244	0.0782	0.0653	0.0029	4e-04	0.0044	0.004
	(0.011)	(0.0118)	(0.0494)	(0.0548)	(0.0323)	(0.0339)	(0.0364)	(0.0428)	(0.0209)	(0.0164)	(0.0534)	(0.0825)	(0.0031)	(0.0031)	(0.0052)	(0.0054)
$PR^{\tau,dw}_{i,t-1}$	0.1399	-0.0157	0.4922	0.1913	0.299	-0.0805	0.7384.	0.0626	0.1619	0.3589*	-1.003.	-0.8996	-0.005	-0.0166	0.0637	0.0939*
	(0.1577)	(0.0926)	(0.5016)	(0.4389)	(0.3487)	(0.2779)	(0.4425)	(0.3526)	(0.1698)	(0.1582)	(0.6092)	(0.7414)	(0.0308)	(0.0293)	(0.0579)	(0.0374)
$Spill(A)^{\mu,up}_{i,t-1}$	-0.0065	-0.0023	0.0194	0.0535	-0.085	-0.1022	-0.0321	-0.0941	0.0486	0.0291	-0.2236.	-0.1688	-0.0035	-0.0018	-0.0106	-0.0075
	(0.0228)	(0.0197)	(0.0953)	(0.1056)	(0.073)	(0.0667)	(0.0924)	(0.0812)	(0.0345)	(0.0332)	(0.1156)	(0.1537)	(0.0065)	(0.006)	(0.0098)	(0.0096)
$Spill(A)^{\mu,dw}_{i,t-1}$	-0.0223	0.0054	0.0348	0.0613	-0.0138	-0.0043	0.006	0.028	-0.0038	-0.0045	-0.0617	-0.0703	-0.0061	-0.0039	-0.008	-0.0052
	(0.0143)	(0.0139)	(0.0716)	(0.0673)	(0.046)	(0.0513)	(0.0561)	(0.0653)	(0.026)	(0.0259)	(0.094)	(0.1276)	(0.0041)	(0.0047)	(0.0076)	(0.0073)
$Spill(A)^{\tau,up}_{i,t-1}$	-0.1603	-1	-1.109	-2.832	-3.598	-5.354.	1.017	-6.405.	1.578	2.85*	-3.161	-4.32	-0.7326**	-0.3763	-1.012**	-0.7787.
	(0.9856)	(0.8618)	(4.315)	(4.866)	(3.29)	(2.957)	(3.697)	(3.878)	(1.687)	(1.357)	(6.068)	(8.63)	(0.2611)	(0.2475)	(0.3789)	(0.4169)
$Spill(A)^{\tau,dw}_{i,t-1}$	0.0371	0.0349	0.4588.	0.2432	0.2026	0.0271	0.489*	0.1453	0.127	0.0485	0.1322	0.4282	-0.0097	-0.0015	0.005	0.0114
	(0.0652)	(0.0499)	(0.2529)	(0.258)	(0.1997)	(0.1919)	(0.1991)	(0.1978)	(0.0983)	(0.086)	(0.324)	(0.4022)	(0.0146)	(0.0165)	(0.0259)	(0.02)
AR(1)	1e-04	0	0.001	1e-04	0.2033	0.3687	5e-04	0	0.5601	0.0526	1e-04	0.0058	0.0032	0	0.0016	0
AR(2)	0.0048	0.0042	0.0097	0.0202	0.0182	0.052	0.0737	0.1603	0.0468	0.0396	0.0468	0.0405	0.5783	0.71	0.1537	0.0632
Sargan	4e-04	3e-04	6e-04	3e-04	3e-04	1e-04	1e-04	0	0.0014	0.019	0.0086	0	0.0803	0.1101	0.08	0.0966
Controls		Y		Y		Y		Y		Y		Y		Y		Y
R^2	0.1577	0.2142	0.2154	0.1667	0.2476	0.2564	0.2801	0.2852	0.1884	0.2518	0.0432	0.0688	0.019	0.0212	0.0028	0.0102

1977-1992 Notes: The table shows the regression results of productivity, labor demand, capital use, and production labor on demand-pull and technology-push effects. The estimation is based on a two-ways Arellano-Bond (AB) first-difference model. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009).

Table C.11: Productivity, labor, capital, and production labor — first subperiod.

	Productivity				Labor & Wages				Capital & Investment				Production labor			
	$TFP_{i,t}$	$TFP_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$L_{i,t}$	$L_{i,t}$	$W_{i,t}$	$W_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$A^{\mu}_{i,t-1}$	0.0624*	0.045.	-0.1046	-0.18	-0.2117**	0.0222	-0.2794**	-0.2751**	0.1597***	-0.0168	0.3646*	0.1793	-0.0201**	-0.0143.	-0.0236*	-0.0139
	(0.0247)	(0.0258)	(0.1232)	(0.1252)	(0.0795)	(0.0866)	(0.1061)	(0.1062)	(0.0349)	(0.034)	(0.1617)	(0.1757)	(0.0069)	(0.0078)	(0.0118)	(0.0134)
$A^{\tau}_{i,t-1}$	0.0812	0.068	-0.038	0.0484	-0.8527***	-0.2916	-0.3586	-0.2032	0.3294***	0.0469	-0.5414	-0.2627	-0.0322.	-0.0273	-0.0544.	-0.0175
	(0.0568)	(0.0559)	(0.2749)	(0.2792)	(0.1933)	(0.1873)	(0.233)	(0.2369)	(0.0869)	(0.0756)	(0.3925)	(0.3917)	(0.0174)	(0.0175)	(0.0293)	(0.0299)
$PR^{\mu,up}_{i,t-1}$	7e-04	-0.0062	0.0901.	0.0806	0.0439	0.0255	0.0538	0.0502	-0.0157	4e-04	0.1444.	0.125.	0.0045	0.004	0.0071	0.0069
	(0.0097)	(0.0093)	(0.0517)	(0.0514)	(0.0366)	(0.0345)	(0.0438)	(0.0436)	(0.0165)	(0.0139)	(0.074)	(0.0721)	(0.0033)	(0.0032)	(0.0056)	(0.0055)
$PR^{\mu,dw}_{i,t-1}$	-0.0101	-0.0056	0.0474	0.045	0.0655*	0.0624*	0.077*	0.0718*	0.0123	-0.0151	0.1616**	0.142**	-0.0051*	-0.0033	-3e-04	-7e-04
	(0.0084)	(0.0082)	(0.038)	(0.0385)	(0.0272)	(0.0258)	(0.0322)	(0.0326)	(0.0122)	(0.0105)	(0.0549)	(0.0539)	(0.0024)	(0.0024)	(0.0041)	(0.0041)
$PR^{\tau,dw}_{i,t-1}$	0.0186	0.0183	0.344*	0.4048*	0.2821*	0.3528***	0.3352*	0.3485**	-0.0487	-0.108*	0.7479***	0.6452**	-0.0045	-0.0073	0.0025	0.0018
	(0.0321)	(0.0313)	(0.1577)	(0.1597)	(0.112)	(0.1061)	(0.1334)	(0.1346)	(0.0499)	(0.0429)	(0.2236)	(0.2227)	(0.0099)	(0.0099)	(0.0169)	(0.017)
$Spill(A)^{\mu,up}_{i,t-1}$	-0.0106	0.0177	0.0841	0.0908	-0.0373	-0.1198	-0.0062	-0.0436	0.1133.	0.0512	0.3041	0.2015	-0.0055	-4e-04	0.0106	0.0031
	(0.0356)	(0.0342)	(0.1851)	(0.1846)	(0.1313)	(0.1233)	(0.1569)	(0.1567)	(0.059)	(0.05)	(0.2654)	(0.2591)	(0.0117)	(0.0116)	(0.0199)	(0.0198)
$Spill(A)^{\mu,dw}_{i,t-1}$	-0.0125	-0.0015	0.068	0.0938	0.0626	0.0656	0.1125*	0.1119*	0.0284	-0.0162	0.1453	0.1259	-0.0064	-0.0042	0.002	0.0021
	(0.0124)	(0.012)	(0.0623)	(0.0622)	(0.0443)	(0.0416)	(0.0527)	(0.0527)	(0.0198)	(0.0168)	(0.0895)	(0.0872)	(0.0039)	(0.0039)	(0.0067)	(0.0067)
$Spill(A)^{\tau,up}_{i,t-1}$	0.2507	0.1165	2.111	2.194.	0.4105	1.458.	0.5583	0.7734	-0.2876	-0.3668	5.391**	5.734**	0.0741	0.082	-0.2779.	-0.1985
	(0.2681)	(0.2613)	(1.32)	(1.317)	(0.9356)	(0.8823)	(1.119)	(1.117)	(0.4207)	(0.3562)	(1.885)	(1.847)	(0.0836)	(0.0825)	(0.1423)	(0.1409)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0296	-0.022	-0.0187	-0.0262	0.0554	-0.0215	0.0219	-0.0128	-0.0017	0.0232	0.1863	0.14	-4e-04	0.0022	-0.0042	-0.0081
	(0.0204)	(0.0195)	(0.1)	(0.0997)	(0.0709)	(0.0666)	(0.0848)	(0.0847)	(0.0319)	(0.027)	(0.1429)	(0.14)	(0.0063)	(0.0063)	(0.0108)	(0.0107)
Controls		Y		Y		Y		Y		Y		Y		Y		Y
R^2	0.8645	0.8775	0.9242	0.9264	0.9511	0.9577	0.9442	0.9456	0.9406	0.9583	0.8871	0.8939	0.9317	0.9343	0.7803	0.7885

Notes: The table shows the regression results of productivity, labor demand, capital use, and production labor on demand-pull and technology-push effects. The estimation is based on a two-ways weighted fixed-effects (FE) model. The weights used in the regressions are $A^{\mu}_{i,t}$ in the TFP regression and $L_{i,t}$ in all other regressions. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The data includes only the first subperiod.

Table C.12: Productivity, labor, capital, and production labor — second subperiod.

	Productivity				Labor & Wages				Capital & Investment				Production labor			
	$TFP_{i,t}$	$TFP_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$L_{i,t}$	$L_{i,t}$	$W_{i,t}$	$W_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$A^{\mu}_{i,t-1}$	0.0382.	0.0363.	-0.0647	-0.0261	-0.1156*	-0.053	-0.1357*	-0.103	0.053.	0.0187	-0.1321	-0.1174	-0.0064	-0.0113.	-0.0067	-0.0095
	(0.0214)	(0.0203)	(0.0786)	(0.0783)	(0.0572)	(0.0566)	(0.0655)	(0.0649)	(0.0317)	(0.0306)	(0.1167)	(0.1158)	(0.0058)	(0.0059)	(0.0106)	(0.0104)
$A^{\tau}_{i,t-1}$	0.0749	0.0433	-0.0348	0.0914	-0.1823	0.0413	0.2227	0.1768	0.2483*	0.171	-0.3939	0.0974	-0.1102***	-0.084***	-0.0569	-0.015
	(0.0841)	(0.082)	(0.2989)	(0.3077)	(0.2217)	(0.2241)	(0.2496)	(0.2557)	(0.1224)	(0.1206)	(0.4499)	(0.456)	(0.0225)	(0.0231)	(0.041)	(0.0411)
$PR^{\mu,up}_{i,t-1}$	0.0025	0.0043	0.026	0.021	0.0182	0.0121	0.0452*	0.0386.	0.0054	0.002	0.0228	0.0306	0.0012	0.0012	0.0066*	0.0067*
	(0.0066)	(0.0063)	(0.0243)	(0.024)	(0.0179)	(0.0174)	(0.0203)	(0.02)	(0.0099)	(0.0094)	(0.0366)	(0.0356)	(0.0018)	(0.0018)	(0.0033)	(0.0032)
$PR^{\mu,dw}_{i,t-1}$	0.0043	0.0092.	0.0356.	0.0453*	0.0215	0.0174	0.0238	0.026	-0.0025	0	0.0672*	0.0571.	4e-04	0.0011	-7e-04	-4e-04
	(0.0057)	(0.0055)	(0.0213)	(0.0213)	(0.0157)	(0.0153)	(0.0178)	(0.0176)	(0.0087)	(0.0083)	(0.032)	(0.0314)	(0.0016)	(0.0016)	(0.0029)	(0.0028)
$PR^{\tau,dw}_{i,t-1}$	0.0403	0.0138	-0.1792	-0.1153	-0.2961***	-0.1067	0.0137	0.0439	0.2378***	0.0961.	-0.2555	0.1664	-0.0062	-0.0052	0.0421**	0.0589***
	(0.0339)	(0.0338)	(0.1212)	(0.1253)	(0.0875)	(0.0916)	(0.1018)	(0.1043)	(0.0493)	(0.0495)	(0.1795)	(0.1859)	(0.009)	(0.0094)	(0.0161)	(0.0167)
$Spill(A)^{\mu,up}_{i,t-1}$	-0.0074	-0.0084	-0.0855.	-0.099*	-0.0605.	-0.051	-0.0545	-0.0581	0.0375*	0.0222	-0.1449*	-0.1296.	-0.0036	-0.005	0.0109.	0.0111.
	(0.0122)	(0.0116)	(0.0467)	(0.0464)	(0.0344)	(0.0334)	(0.0391)	(0.0385)	(0.0191)	(0.0181)	(0.0703)	(0.0687)	(0.0035)	(0.0035)	(0.0064)	(0.0062)
$Spill(A)^{\mu,dw}_{i,t-1}$	-0.0143.	-0.0098	-0.0135	-0.0209	0.0079	-0.002	-0.0026	-0.0072	-0.0119	-0.0065	0.0236	7e-04	-0.0011	-3e-04	0.0012	0.001
	(0.0086)	(0.0082)	(0.0316)	(0.0313)	(0.0233)	(0.0226)	(0.0264)	(0.026)	(0.0129)	(0.0123)	(0.0474)	(0.0464)	(0.0024)	(0.0024)	(0.0043)	(0.0042)
$Spill(A)^{\tau,up}_{i,t-1}$	-0.8952**	-0.7984*	-3.417**	-3.681**	-2.234*	-2.566**	-3.156**	-3.433***	0.928.	0.903.	-2.214	-2.735	-0.3505***	-0.3291***	-0.2169	-0.2245
	(0.3441)	(0.3262)	(1.23)	(1.221)	(0.9085)	(0.8841)	(1.028)	(1.016)	(0.5075)	(0.4811)	(1.853)	(1.812)	(0.0925)	(0.0918)	(0.1675)	(0.1632)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0187	-0.0357	-0.0887	-0.0904	-0.0303	-0.0211	-0.0743	-0.0538	-0.034	-0.0081	0.0859	0.1276	0.0082	0.0084	-0.0117	-0.0099
	(0.0293)	(0.0278)	(0.11)	(0.1088)	(0.0812)	(0.079)	(0.0919)	(0.0904)	(0.045)	(0.0429)	(0.1654)	(0.1612)	(0.0083)	(0.0082)	(0.015)	(0.0145)
Controls		Y		Y		Y		Y		Y		Y		Y		Y
R^2	0.7926	0.8174	0.925	0.928	0.9423	0.9469	0.9442	0.9468	0.9207	0.9298	0.8616	0.8703	0.8892	0.8933	0.6905	0.7112

Notes: The table shows the regression results of productivity, labor demand, capital use, and production labor on demand-pull and technology-push effects. The estimation is based on a two-ways weighted fixed-effects (FE) model. The weights used in the regressions are $A^{\mu}_{i,t}$ in the TFP regression and $L_{i,t}$ in all other regressions. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The data includes only the second subperiod.

Supplementary Material

SI.1. Data processing in detail

This analysis builds on two distinct sources of data brought into a consistent form that enables the statistical analyses; this is (1) a series of time snapshots of the network of cross-industrial IO flows and patent citations and (2) a panel data set of aggregate statistical indicators at the industry level. Industries are identified by 6-digit NAICS codes. The time snapshots cover 5-year intervals from 1977 to 2012. Obtaining these data involved a series of steps of re-formatting and harmonization, which are explained in detail below.

SI.1.1. Input-output data

The IO data is constructed by the composition and harmonization of the historical benchmark tables provided by Bureau of Economic Analysis (BEA).[22] Since 1947, BEA publishes IO tables at the detailed industry level every five years. The data is collected in BEA's quinquennial Survey of Current Business. A detailed manual on BEA's IO data is provided by Horrowitz and Planting (2006)

SI.1.1.1. Overview

The raw data shows monetary transactions between industries. It covers also final demand sectors and public services. For this project, I use tables from 1977-2012. I made a series of conversions and processing steps to harmonize the data. Over time, industrial classification systems and technical methods of data processing, formatting and saving have changed. The earliest tables are only available in text format that I edited manually to make it readable for statistical software. A further challenge arises from changes in the classification system, which are most pronounced in the conversion from SIC to NAICS.

The final data structure is a series of quadratic matrices for each period that show the monetary transactions between industries in NAICS 2002 codes. The data is also used to create a panel of industry level indicators, i.e. outputs, inputs, and growth rates.

[22] https://www.bea.gov/industry/historical-benchmark-input-output-tables [accessed on Dec 21, 2020]

SI.1.1.2. Processing steps in detail

Here, I explain single steps of data processing.

Step 1: For each period, the IO data is downloaded separately. Some manual harmonization and data conversions were made to obtain machine-readable, harmonized data tables. For example, the very old data is only available in text format, which is not ready to be read by statistical software. The more recent table are Excel files with many macros and explanations in text. All tables were reformatted individually. The scripts are available in the data publication. After this step, all tables have a uniform format, which is a long 3-column table with column (1) as producer ID, column (2) as user ID, and column (3) indicating the monetary value of the goods that flow from producer to user.

Step 2: I created large quadratic matrices with rows as producers and columns as users. The entries $flow_{ij,t}^{out,\mu}$ are flows of goods from i to j. Hence, column-wise reading indicates the composition of inputs used by sector j and row-wise reading indicates the composition of customer industries to which industry i delivers.

Step 3: This is an intermediate step. All concordance and IO-to-industry conversion tables have to be harmonized. Again, some of the data is not machine readable. Moreover, all codes need to be harmonized to obtain a mapping from IO codes for each period to 2002-NAICS codes. Some of the IO codes map to multiple industries. In this step, tables were created where each row indicates an IO code and all NAICS codes that are attributed to the respective IO.

Step 4: NAICS-based IO tables were harmonized and consistency checks were done. For example, I tested whether the differences in the tables e.g. regarding the sector coverage are negligible. Some normalizations of IO-flows to input (output) shares were made through division by row (column) sum. The full 6-digit list is used as row and column names.

Not every time snapshot has a full sector coverage. This is a result of reclassification issues, obsolescence, and introduction of new sectors. For example, some of the finely granulate computer industries were not yet existing in 1977. For these cases, empty vectors are included to present missing sectors to ensure that matrices have same dimensionality.

Additional steps of harmonization are done. Rows represent the range of inputs that is used, columns represent customers. After this step, NAICS 6-digit data

on IO flows, sector weights (row and column sums), input shares (measured in percentage points), 6-digit distance matrix computed by the input-share dissimilarity are obtained.

Step 5: I harmonized the data to quadratic NAICS 2002 matrices. The matrices are 1179 × 1179 matrices of 6-digit industries.[23] Empty rows and columns are included for industries that are not producing in some t, for example if an industry was not yet existing or disappeared over time.

Step 6: For each t, I create NAICS × NAICS matrices with flows of goods $flow^{\mu}_{ij,t}$ as entries.

SI.1.1.3. Technical and conceptual issues

General remarks about IO codes, NAICS and SIC The original IO data in early years uses IO codes, which are an internal metric of the accounting system used to construct social accounting matrices (SAM). These codes are converted into industry codes (SIC and NAICS). The classification system has changed over time. Fortunately, the IO-codes in the raw IO tables are largely consistent across time. I converted the accounting codes into SIC and from SIC into NAICS or directly into NAICS if such mapping is available. For the data harmonization, I converted all codes into the NAICS-2002 codes as they can be directly mapped to SIC 1987 codes.

How to deal with accounting codes that are mapped into multiple SIC sectors? Some of the accounting codes are associated with multiple SIC sectors, i.e. multiple industries have been aggregated into one accounting position. Information about the strengths of links to each of these these subsectors is missing. For reasons of simplification, I assume that the accounting position is equally related to all of them. The strengths of single links is weighted uniformly by the number of sectors. For example, the IO code 020401 ("Fruits") is linked to 9 SIC sectors (0171, 0172, 0174, 0175, *0179, *019, *0219, *0259, *029). The links are weighted by factor 1/9.

How to deal with inconsistencies across time in changing classification systems? The accounting codes of 1977 and 1982 data is mapped to SIC 1987. All mappings from accounting positions to SIC are based on the 1987 data after having ensured that the accounting codes are consistent across time. Also the vast majority

[23] 473 of 1179 NAICS 6-digit codes are manufacturing and out of these, 307 provide sufficient data to form a balanced panel. These 307 industries are used in the final analyses.

of IO-to-SIC-mappings is consistent in 1977 and 1992 data. For 1977 some minor deviations exist but these can be largely explained by adjustments in the SIC system between 1977 to 1987. Some of the old SIC industries do not exist any longer. A reconstruction is practically not feasible with reasonable effort given that the expected value added of higher precision is negligibly small if existing at all. The 1977 IO-SIC mapping is only used when 1987-data is not available.

In the 2002 NAICS file, some IO codes are mapped to a very high number of sub-sectors. This is for example the case for aggregate positions such as retail and wholesale trade and construction. I kept them in the mapping. It should be noted that an accounting position that has a link to more than hundred 6-digit NAICS industries is not necessarily meaningful. I cope with this problem by a series of robustness checks using only a subset of the data, higher levels of aggregation and rounding of IO links that fall below a certain threshold.

The more recent versions of the classification systems are more detailed. I used equal weights when one coarse industry mapped to several more detailed industry when using another (typically more recent) classification system. Hence, the transaction volume is equally distributed across sub-sectors.

SI.1.2. Patent data

SI.1.2.1. Overview

The raw patent data classified by CPC codes are taken from an earlier project. An extensive documentation of the data is provided along with the data, which can be downloaded for reuse under a CC-BY-4.0 license (Hötte, 2021).

From the raw data, I use the CPC classification data, citations among patents with the grant number as ID, and data on the grant year of the patents. Further, to map patents classified by CPC codes to NAICS 6-digit codes, I used the concordance tables by Goldschlag et al. (2020).[24]. I used the *Cooperative Patent Classification (CPC) Crosswalks - Version 1603* file downloaded in October 2021.

The patents were first reclassified into NAICS taking account of the weighting scheme of Goldschlag et al.'s (2020) concordance. Next, a NAICS-to-NAICS citation network for each 5-year time window was constructed.

[24] https://sites.google.com/site/nikolaszolas/PatentCrosswalk [accessed in Oct 2021]

SI.1.2.2. Processing steps in detail

To construct a patent citation networks among NAICS 6-digit industries, the data were processed in a series of steps.

Step 1: In a first step, I mapped patents to NAICS 2002 codes to create industry level patent stocks as 5-year aggregates covering the period 1973-2012. First, patents were sampled by time window. Then, patents in each time window were aggregated into each 4-digit CPC class ensuring uniqueness for each entry by patent grant number and CPC 4-digit code. Hence, patents that map to multiple more disaggregate CPC codes that belong to the same 4-digit aggregate were treated as unique entry. The counts at the 4-digit CPC level were subsequently mapped to NAICS 6-digit codes taking account of the weights, i.e. the patent counts are multiplied by the weight whenever one CPC 4-digit class maps to multiple NAICS 6-digit codes.

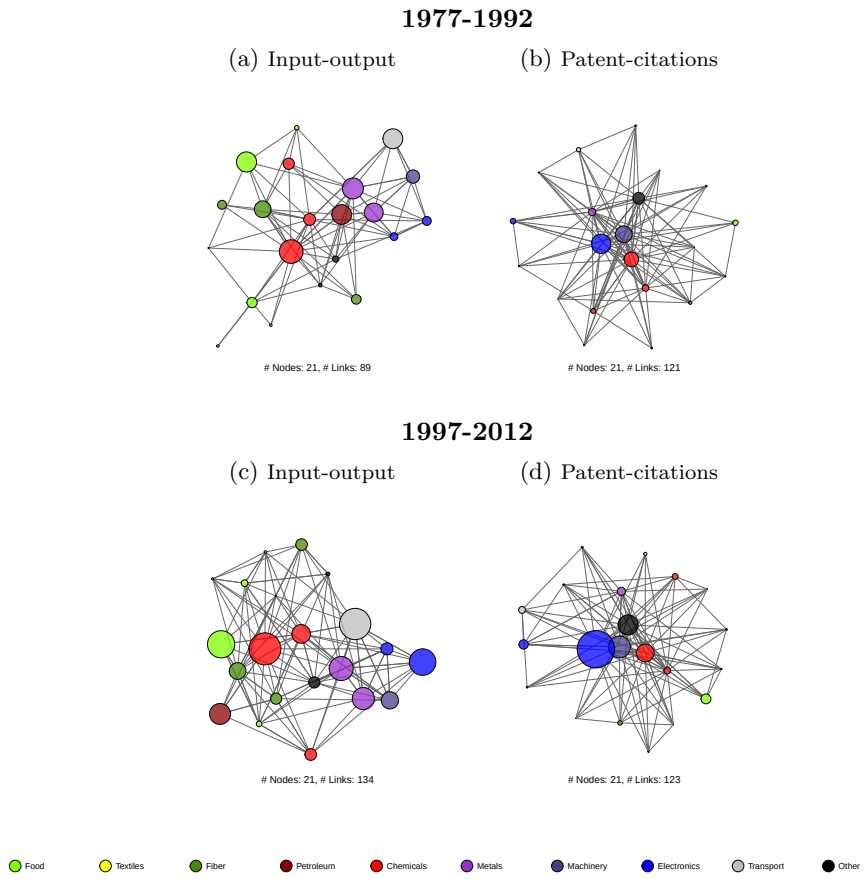
Step 2: Next, the citation data is mapped from citations between individual patents by grant number to citations between NAICS 6-digit industries. The NAICS-to-NAICS edgelist also contains a column with the weight, which indicates the number of citations that flow from one industry to another during each 5-year time window. To obtain this edgelist, both the citing and the cited patent were first mapped to CPC ensuring the uniqueness of patent CPC 4-digit links. Then, I aggregated them and obtained the number of CPC 4-digit-to-CPC 4-digit citations based on unique pairs of patents. Next, I mapped the CPC-to-CPC citations to NAICS while applying the weight to both the citing and cited NAICS industry.

Step 3: The edgelist is used to construct an adjacency matrix with 6-digit industries as row and column names. The data is harmonized with the format of the IO adjacency matrices. Additionally, the adjacency matrices are also created for other levels of aggregation.

SI.2. Supplementary descriptives

SI.2.1. Network plots

Figure SI.1: Upstream networks at the 3-digit level for different periods



Notes: These figures show the network of upstream links (suppliers) at the 4-digit level for two different time periods. A link between a pair of industries i and j is shown if j is a sufficiently important supplier to i, i.e. if the average of the weight $w_{ij,t}^{in,\alpha}$ during time periods 1977-1992 and 1997-2012 exceeds a threshold level given by the average weight over all industry pairs and all periods plus one standard deviation ($\text{mean}_{i,j,t}(w_{ij,t}^{in,\alpha}) + \text{sd}_{i,j,t}(w_{ij,t}^{in,\alpha})$). The size of the nodes is proportional to the size of an industry $A_{i,t}^{\alpha}$ in the respective layer. The figure is generated using the plotting functions of the R-package *igraph*, which makes use of the Fruchtermann-Reingold algorithm to allocate the nodes and edges of the network. Self-citations and within-sector IO flows are not shown. The colors indicate broad industrial categories given by groups of 3-digit level industries, i.e. Food (311-312), Textiles (314-316), Fiber (321-323), Petroleum (324), Chemicals (325-327), Metals (331,332), Machinery (333), Electronics (334-335), Transport (336), Other (337-339).

SI.2.2. Industry rankings

Tables SI.1 and SI.2 show the Top-10 ranking of industries by up- and downstream centrality as measured by the PageRank.

Table SI.1: Top-10 ranking of industries by the upstream PageRank at the 6-digit level.

	Top-10 industries by Pagerank ($PR_{i,t}^{\mu,up}$)											
	1977-1982			1987-1992			1997-2002			2007-2012		
1	Petroleum Refineries	324110	0.17	Petroleum Refineries	324110	0.08	Petroleum Refineries	324110	0.10	Copper Refineries	331411	0.05
2	Copper Refineries	331411	0.05	Plastics Mat. & Resin	325211	0.05	Iron & Steel Mills	331111	0.07	Iron & Steel Mills	331111	0.05
3	Plastics Mat. & Resin	325211	0.04	Copper Refineries	331411	0.05	Semiconductor & Device	334413	0.05	Automobile Mnft.	336111	0.03
4	All Petrol. & Coal Prod.	324199	0.04	All Petrol. & Coal Prod.	324199	0.04	Sawmills	321113	0.04	Biological Prod.	325414	0.02
5	Iron & Steel Mills	331111	0.04	Chem. Preparations	325998	0.03	Plastics Mat. & Resin	325211	0.04	Plastics Mat. & Resin	325211	0.02
6	Chem. Preparations	325998	0.02	Iron & Steel Mills	331111	0.03	Copper Refineries	331411	0.03	Ship Building & Repair	336611	0.02
7	Paperboard Mills	322130	0.02	Inorganic Dye & Pigm.	325131	0.03	Gum & Wood Chem.	325191	0.02	Aircraft Mnft.	336411	0.02
8	Organic Chem.	325199	0.02	Organic Chem.	325199	0.03	Organic Chem.	325199	0.02	Dog & Cat Food Mnft.	311111	0.02
9	Inorganic Dye & Pigm.	325131	0.01	Fats & Oils Refin.	311225	0.01	Machine Shops	332710	0.02	Petroleum Refineries	324110	0.01
10	Metal Can Mnft.	332431	0.01	Nitrogen. Fertl. Mnft.	325311	0.01	Print Circuit Assembly	334418	0.02	Semiconductor & Device	334413	0.01
	Quartiles:											
	0.01, 0.01, 0.01			0.01, 0.01, 0.01			0.01, 0.01, 0.02			0.01, 0.01, 0.01		

	Top-10 industries by Pagerank ($PR_{i,t}^{\tau,up}$)											
	1977-1982			1987-1992			1997-2002			2007-2012		
1	Adhesive Mnft.	325520	0.05	Adhesive Mnft.	325520	0.05	Semiconductor & Device	334413	0.05	Semiconductor & Device	334413	0.06
2	Chem. Preparations	325998	0.05	Chem. Preparations	325998	0.05	Adhesive Mnft.	325520	0.05	Adhesive Mnft.	325520	0.04
3	Semiconductor & Device	334413	0.03	Semiconductor & Device	334413	0.04	Chem. Preparations	325998	0.04	Electr. Computer Mnft.	334111	0.04
4	Power Transm. Equ.	333613	0.03	Power Transm. Equ.	333613	0.03	Laboratory Apparatus	339111	0.03	Chem. Preparations	325998	0.04
5	Fastener & Pin	339993	0.02	Fastener & Pin	339993	0.03	Electr. Computer Mnft.	334111	0.03	Optical Instrum. & Lens	333314	0.03
6	Laboratory Apparatus	339111	0.02	Electr. Computer Mnft.	334111	0.03	Fastener & Pin	339993	0.03	Fastener & Pin	339993	0.03
7	Speed Changer & Gear	333612	0.02	Laboratory Apparatus	339111	0.02	Optical Instrum. & Lens	333314	0.02	Wireless Communic.	334220	0.02
8	Electr. Computer Mnft.	334111	0.02	Speed Changer & Gear	333612	0.02	Power Transm. Equ.	333613	0.02	Medical Instrum.	339112	0.02
9	Boiler & Heat Exch.	332410	0.02	Optical Instrum. & Lens	333314	0.02	Speed Changer & Gear	333612	0.02	Power Transm. Equ.	333613	0.02
10	Optical Instrum. & Lens	333314	0.02	Boiler & Heat Exch.	332410	0.02	Dental Equ. & Supplies	339114	0.02	Elctrmed. Apparatus	334510	0.02
	Quartiles:											
	0.01, 0.01, 0.0125			0.01, 0.01, 0.01			0.01, 0.01, 0.01			0.01, 0.01, 0.02		

Notes: Industries are ranked by the PageRank compiled on upstream links $PR_{i,t}^{\alpha,up}$ averaged across the time window indicated in the column header in decreasing order, i.e. showing the largest industries on top. The 6-digit number in the second column of each block shows the NAICS code of the corresponding industry and the third column shows the value of $PR_{i,t}^{\alpha,up}$. The values $PR_{i,t}^{\alpha,up}$ were normalized before through division by the economy-wide average in t, i.e. the mean value for each period equals one. The bottom lines of each sub-table show the quartile values as indicators for the skewness of the distribution. Deviations of the median from the average indicate skewness.

Table SI.2: Top-10 ranking of industries by the downstream PageRank at the 6-digit level.

	Top-10 industries by Pagerank ($PR_{i,t}^{\mu,dw}$)											
	1977-1982			1987-1992			1997-2002			2007-2012		
1	Mobile Home Mnft.	321991	0.07	Motor Home Mnft.	336213	0.10	Aircraft Mnft.	336411	0.04	Petroleum Refineries	324110	0.07
2	Motor Home Mnft.	336213	0.04	Ice & Frozen Dessert	311520	0.04	Mobile Home Mnft.	321991	0.04	Copper Refineries	331411	0.06
3	Frozen Spec. Food Mnft.	311412	0.03	Mobile Home Mnft.	321991	0.04	Automobile Mnft.	336111	0.04	Iron & Steel Mills	331111	0.04
4	Motor Vhcl. Body Mnft.	336211	0.03	Missile & Space Vhcl.	336414	0.03	Motor Home Mnft.	336213	0.03	Die-Cut & Paper Office	322231	0.03
5	Missile & Space Vhcl.	336414	0.03	Aircraft Mnft.	336411	0.03	Ship Building & Repair	336611	0.03	Plastics Mat. & Resin	325211	0.02
6	Ice & Frozen Dessert	311520	0.03	Motor Vhcl. Body Mnft.	336211	0.02	Retail Bakeries	311811	0.03	Soybean Processing	311222	0.02
7	Ship Building & Repair	336611	0.02	Frozen Spec. Food Mnft.	311412	0.02	Commercial Bakeries	311812	0.03	All Misc. Electr. Equ.	335999	0.01
8	Automobile Mnft.	336111	0.02	Ship Building & Repair	336611	0.02	Travel Trailer & Camper	336214	0.02	Graphite Prod.	335991	0.01
9	Light & Utility Truck	336112	0.02	Travel Trailer & Camper	336214	0.02	Oth. Animal Food Mnft.	311119	0.02	Motor Vhcl. Air-Cond.	336391	0.01
10	Heavy Duty Truck Mnft.	336120	0.02	Electr. Computer Mnft.	334111	0.02	Dog & Cat Food Mnft.	311111	0.02	Gum & Wood Chem.	325191	0.01
	Quartiles:											
	0.01, 0.01, 0.02			0.01, 0.01, 0.02			0.01, 0.01, 0.01			0.01, 0.01, 0.01		

	Top-10 industries by Pagerank ($PR_{i,t}^{\tau,dw}$)											
	1977-1982			1987-1992			1997-2002			2007-2012		
1	Adhesive Mnft.	325520	0.05	Adhesive Mnft.	325520	0.05	Semiconductor & Device	334413	0.05	Semiconductor & Device	334413	0.07
2	Chem. Preparations	325998	0.05	Chem. Preparations	325998	0.05	Adhesive Mnft.	325520	0.05	Electr. Computer Mnft.	334111	0.04
3	Semiconductor & Device	334413	0.04	Semiconductor & Device	334413	0.04	Chem. Preparations	325998	0.05	Adhesive Mnft.	325520	0.04
4	Power Transm. Equ.	333613	0.03	Power Transm. Equ.	333613	0.03	Electr. Computer Mnft.	334111	0.03	Chem. Preparations	325998	0.04
5	Fastener & Pin	339993	0.03	Fastener & Pin	339993	0.03	Fastener & Pin	339993	0.03	Optical Instrum. & Lens	333314	0.03
6	Electr. Computer Mnft.	334111	0.02	Electr. Computer Mnft.	334111	0.03	Optical Instrum. & Lens	333314	0.02	Fastener & Pin	339993	0.03
7	Speed Changer & Gear	333612	0.02	Speed Changer & Gear	333612	0.02	Power Transm. Equ.	333613	0.02	Power Transm. Equ.	333613	0.02
8	Urethane & Foam Prod.	326150	0.02	Optical Instrum. & Lens	333314	0.02	Speed Changer & Gear	333612	0.02	Medical Instrum.	339112	0.02
9	Boiler & Heat Exch.	332410	0.02	Boiler & Heat Exch.	332410	0.02	Urethane & Foam Prod.	326150	0.01	Misc. Food Mnft.	311999	0.02
10	Optical Instrum. & Lens	333314	0.02	Urethane & Foam Prod.	326150	0.02	Dental Equ. & Supplies	339114	0.01	Watch & Clock Mnft.	334518	0.02
	Quartiles:											
	0.01, 0.01, 0.01			0.01, 0.01, 0.01			0.01, 0.01, 0.01			0.01, 0.01, 0.0175		

Notes: Industries are ranked by the PageRank compiled on downstream links $PR_{i,t}^{\alpha,dw}$ averaged across the time window indicated in the column header in decreasing order, i.e. showing the largest industries on top. The 6-digit number in the second column of each block shows the NAICS code of the corresponding industry and the third column shows the value of $PR_{i,t}^{\alpha,dw}$. The values $PR_{i,t}^{\alpha,dw}$ were normalized before through division by the economy-wide average in t, i.e. the mean value for each period equals one. The bottom lines of each sub-table show the quartile values as indicators for the skewness of the distribution. Deviations of the median from the average indicate skewness.

SI.3. Disentangled technology-push and demand-pull and the direction of change

In this section, I provide additional results for the effects of TP and DP on productivity (TFP and labor productivity), labor demand (employment and wages), capital use (capital intensity and investment per capita), and production labor (share of production workers and relative wage paid for production labor).

The tables below show the effects from a weighted FE regression, analogous to the extract of the results shown in the main text 5.2.2. Additional results relying on dynamic panels methods were used in a comprehensive series of robustness checks. However, as explained above, these models severely suffer from weak instruments. The results should be understood as analysis of conditional correlations without any claims for causality.

Table SI.3: Productivity effects.

	Total factor productivity						Labor productivity					
	$\tau \to TFP_{i,t}$		$\mu \to TFP_{i,t}$		Both		$\tau \to (VA/L)_{i,t}$		$\mu \to (VA/L)_{i,t}$		Both	
	$TFP_{i,t}$	$TFP_{i,t}$	$TFP_{i,t}$	$TFP_{i,t}$	$TFP_{i,t}$	$TFP_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$	$(VA/L)_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$TFP_{i,t-1}$	0.9532***	0.8322***	0.9584***	0.8454***	0.9444***	0.8321***						
	(0.016)	(0.0245)	(0.0155)	(0.0244)	(0.0162)	(0.0246)						
$(VA/L)_{i,t-1}$							0.8092***	0.6916***	0.8066***	0.7052***	0.8153***	0.6924***
							(0.0134)	(0.0421)	(0.0134)	(0.0423)	(0.0143)	(0.0426)
$A^{\mu}_{i,t-1}$	0.0476**	0.0278.			0.0459**	0.0275.	-0.1486*	-0.1468*			-0.1465*	-0.1469*
	(0.0166)	(0.016)			(0.0166)	(0.0159)	(0.0624)	(0.0629)			(0.0624)	(0.0629)
$A^{\tau}_{i,t-1}$			0.098*	0.0058	0.0966*	0.0096			-0.1197	-0.0679	-0.1031	-0.0482
			(0.0452)	(0.0447)	(0.0452)	(0.0446)			(0.1588)	(0.1677)	(0.1587)	(0.1675)
$PR^{\mu,up}_{i,t-1}$	0.0036	0.0082.			0.0034	0.0082.	0.0414*	0.0463*			0.042*	0.047*
	(0.0051)	(0.0048)			(0.0051)	(0.0048)	(0.0196)	(0.0196)			(0.0196)	(0.0196)
$PR^{\mu,dw}_{i,t-1}$	0.006	0.0122**			0.0063	0.0123**	0.044**	0.0557***			0.046**	0.057***
	(0.0043)	(0.0041)			(0.0043)	(0.0041)	(0.0161)	(0.0162)			(0.0162)	(0.0163)
$PR^{\tau,dw}_{i,t-1}$			0.0021	-0.0135	-0.0041	-0.0166			-0.0782	-0.0216	-0.1013	-0.0463
			(0.0195)	(0.0192)	(0.0196)	(0.0192)			(0.073)	(0.0742)	(0.0734)	(0.0745)
$Spill(A)^{\mu,up}_{i,t-1}$	-0.0095	-0.0083			-0.0111	-0.0117	-0.0622	-0.0766.			-0.0742.	-0.0815*
	(0.0103)	(0.0097)			(0.0103)	(0.0097)	(0.0408)	(0.0408)			(0.0412)	(0.0411)
$Spill(A)^{\mu,dw}_{i,t-1}$	-0.0167*	-0.0137*			-0.016*	-0.0135*	-0.0182	-0.02			-0.0161	-0.0176
	(0.0065)	(0.0062)			(0.0065)	(0.0062)	(0.0251)	(0.0251)			(0.0252)	(0.0252)
$Spill(A)^{\tau,up}_{i,t-1}$			-0.7579***	-0.7383***	-0.7711***	-0.7479***			-1.399.	-1.154	-1.471.	-1.207
			(0.2119)	(0.2002)	(0.2122)	(0.2002)			(0.7844)	(0.7871)	(0.7862)	(0.7875)
$Spill(A)^{\tau,dw}_{i,t-1}$			-0.0418*	-0.0235	-0.0424*	-0.0225			0.0353	0.0355	0.0341	0.0382
			(0.0176)	(0.0167)	(0.0176)	(0.0167)			(0.0658)	(0.066)	(0.0659)	(0.066)
$W_{i,t-1}$		0.059***		0.0565***		0.0579***		0.1687***		0.1349**		0.1659***
		(0.009)		(0.009)		(0.0091)		(0.0477)		(0.0477)		(0.048)
$(K/L)_{i,t-1}$		0.0349***		0.0398***		0.0363***		-0.056.		-0.0523.		-0.0544.
		(0.0074)		(0.0077)		(0.0077)		(0.0288)		(0.0297)		(0.0297)
$(L^P/L)_{i,t-1}$		0.1801*		0.141.		0.1587*		1.17***		1.109***		1.114***
		(0.0731)		(0.0735)		(0.0735)		(0.3005)		(0.3041)		(0.304)
$(I/L)_{i,t-1}$		-0.0474***		-0.0473***		-0.0473***		0.0425*		0.0439*		0.0411.
		(0.005)		(0.005)		(0.005)		(0.0211)		(0.0212)		(0.0212)
$(E/L)_{i,t-1}$		-0.0479***		-0.0454***		-0.048***		-0.0848**		-0.0739**		-0.0856**
		(0.0069)		(0.0069)		(0.007)		(0.027)		(0.0273)		(0.0274)
$(M/L)_{i,t-1}$		-0.0019		-0.0021		-0.0012		0.0069		0.0115		0.0118
		(0.0072)		(0.0073)		(0.0073)		(0.0287)		(0.0294)		(0.0294)
$(W^P/W)_{i,t-1}$		0.0369		0.025		0.0349		-0.2304		-0.2732		-0.2356
		(0.0446)		(0.0447)		(0.0446)		(0.1875)		(0.1886)		(0.1882)
Controls		Y		Y		Y		Y		Y		Y
R^2	0.7408	0.7726	0.7413	0.7719	0.7438	0.7746	0.9003	0.9022	0.8998	0.9013	0.9007	0.9024

Notes: The table shows the regression results of total factor productivity TFP and labor productivity $(VA/L)_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways weighted fixed-effects (FE) model. The weights used in the regressions are $A^{\mu}_{i,t}$ in the TFP regression and $L_{i,t}$ in all other regressions. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are TFP, $(VA/L)_{i,t}A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1.

Table SI.4: Labor market outcomes.

	Employment						Wage					
	$\tau \to L_{i,t}$		$\mu \to L_{i,t}$		Both		$\tau \to W_{i,t}$		$\mu \to W_{i,t}$		Both	
	$L_{i,t}$	$L_{i,t}$	$L_{i,t}$	$L_{i,t}$	$L_{i,t}$	$L_{i,t}$	$W_{i,t}$	$W_{i,t}$	$W_{i,t}$	$W_{i,t}$	$W_{i,t}$	$W_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$L_{i,t-1}$	0.8379***	0.9597***	0.8334***	0.968***	0.8415***	0.96***						
	(0.0145)	(0.027)	(0.0145)	(0.0273)	(0.0145)	(0.0275)						
$W_{i,t-1}$		-0.0352*		-0.0498**		-0.0373*	0.8381***	0.8487***	0.8171***	0.8172***	0.8332***	0.8407***
		(0.0171)		(0.0165)		(0.0174)	(0.0122)	(0.0199)	(0.0121)	(0.0194)	(0.0129)	(0.0201)
$A^{\mu}_{i,t-1}$	-0.2697***	-0.09*			-0.2349***	-0.0895*	-0.2236***	-0.2105***			-0.2227***	-0.2082***
	(0.0427)	(0.0438)			(0.0426)	(0.0438)	(0.0526)	(0.0527)			(0.0526)	(0.0527)
$A^{\tau}_{i,t-1}$			-0.4525***	-0.0185	-0.4202***	-0.019			-0.0857	-0.0645	-0.0747	-0.0632
			(0.1158)	(0.117)	(0.1152)	(0.1171)			(0.1344)	(0.1409)	(0.1337)	(0.1402)
$PR^{\mu,up}_{i,t-1}$	0.025.	0.0218			0.0258.	0.0223.	0.0579***	0.059***			0.0585***	0.0596***
	(0.0143)	(0.0135)			(0.0142)	(0.0136)	(0.0166)	(0.0164)			(0.0166)	(0.0164)
$PR^{\mu,dw}_{i,t-1}$	0.0229.	0.0261*			0.024*	0.0265*	0.0363**	0.0399**			0.0371**	0.0398**
	(0.0118)	(0.0112)			(0.0117)	(0.0112)	(0.0136)	(0.0136)			(0.0136)	(0.0136)
$PR^{\tau,dw}_{i,t-1}$			-0.1631**	0.0297	-0.155**	0.0136			0.0563	0.1111.	0.0284	0.0841
			(0.0518)	(0.0511)	(0.052)	(0.0514)			(0.0617)	(0.0622)	(0.0619)	(0.0623)
$Spill(A)^{\mu,up}_{i,t-1}$	-0.0557.	-0.0563*			-0.0743*	-0.0555.	-0.071*	-0.0705*			-0.0718*	-0.0672.
	(0.0298)	(0.0281)			(0.0297)	(0.0284)	(0.0345)	(0.0342)			(0.0348)	(0.0344)
$Spill(A)^{\mu,dw}_{i,t-1}$	0.0076	-0.0092			0.0032	-0.0079	-0.0072	-0.0107			-0.004	-0.0085
	(0.0183)	(0.0174)			(0.0181)	(0.0175)	(0.0212)	(0.0211)			(0.0212)	(0.0212)
$Spill(A)^{\tau,up}_{i,t-1}$			-0.653	-0.434	-0.754	-0.4783			-1.402*	-1.24.	-1.533*	-1.336*
			(0.5688)	(0.5437)	(0.5666)	(0.5451)			(0.6643)	(0.6627)	(0.6627)	(0.661)
$Spill(A)^{\tau,dw}_{i,t-1}$			0.0938.	0.0302	0.0839.	0.0322			0.045	0.0386	0.0474	0.0451
			(0.048)	(0.0459)	(0.0478)	(0.0459)			(0.0558)	(0.0556)	(0.0556)	(0.0554)
$(K/L)_{i,t-1}$		-0.1079***		-0.109***		-0.111***		-0.0502*		-0.0602*		-0.0604*
		(0.0205)		(0.0209)		(0.0209)		(0.0242)		(0.025)		(0.0249)
$(L^P/L)_{i,t-1}$		1.341***		1.345***		1.336***		1.126***		1.167***		1.127***
		(0.207)		(0.209)		(0.209)		(0.2509)		(0.2542)		(0.253)
$(I/L)_{i,t-1}$		0.0609***		0.0614***		0.0605***		0.0715***		0.0772***		0.0718***
		(0.0151)		(0.0151)		(0.0151)		(0.0175)		(0.0177)		(0.0176)
$(E/L)_{i,t-1}$		-0.0483*		-0.0458*		-0.0476*		-0.0885***		-0.0764***		-0.0861***
		(0.0219)		(0.0219)		(0.022)		(0.0224)		(0.0228)		(0.0228)
$(M/L)_{i,t-1}$		-0.0779***		-0.0776***		-0.0769***		0.0195		0.0236		0.0225
		(0.02)		(0.0206)		(0.0206)		(0.0241)		(0.0247)		(0.0247)
$(W^P/W)_{i,t-1}$		-0.4702***		-0.4825***		-0.4672***		-0.3355*		-0.3488*		-0.3293*
		(0.1292)		(0.1297)		(0.1296)		(0.1569)		(0.158)		(0.1571)
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9273	0.9359	0.9276	0.9355	0.929	0.9359	0.9248	0.9266	0.9237	0.9257	0.9251	0.927

Notes: The table shows the regression results of employment $L_{i,t}$ and wages $W_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways weighted fixed-effects (FE) model. The weights used in the regressions are $A^{\mu}_{i,t}$ in the TFP regression and $L_{i,t}$ in all other regressions. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1.

Table SI.5: Effects on capital use.

	Capital intensity						Investment per capita					
	$\tau \to (K/L)_{i,t}$		$\mu \to (K/L)_{i,t}$		Both		$\tau \to (I/L)_{i,t}$		$\mu \to (I/L)_{i,t}$		Both	
	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(K/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$	$(I/L)_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$(K/L)_{i,t-1}$	0.69***	0.0212	0.664***	0.0234	0.6847***	0.0249		-0.325***		-0.3464***		-0.3426***
	(0.0279)	(0.0161)	(0.0277)	(0.0161)	(0.0277)	(0.0162)		(0.0693)		(0.0699)		(0.0698)
$(I/L)_{i,t-1}$		0.0789***		0.0762***		0.0765***	0.2362***	0.1602***	0.2912***	0.1819***	0.23***	0.1708***
		(0.0076)		(0.0076)		(0.0077)	(0.0294)	(0.0393)	(0.0278)	(0.0391)	(0.0298)	(0.0393)
$A^{\mu}_{i,t-1}$	0.1776***	-0.0122			0.1597***	-0.0168	0.3471*	0.1329			0.3646*	0.1793
	(0.0348)	(0.034)			(0.0349)	(0.034)	(0.1622)	(0.1765)			(0.1617)	(0.1757)
$A^{\tau}_{i,t-1}$			0.3533***	0.0565	0.3294***	0.0469			-0.6145	-0.3806	-0.5414	-0.2627
			(0.0875)	(0.0749)	(0.0869)	(0.0756)			(0.3941)	(0.3912)	(0.3925)	(0.3917)
$PR^{\mu,up}_{i,t-1}$	-0.0126	0.0021			-0.0157	4e-04	0.1389.	0.1222.			0.1444.	0.125.
	(0.0166)	(0.0139)			(0.0165)	(0.0139)	(0.0743)	(0.0725)			(0.074)	(0.0721)
$PR^{\mu,dw}_{i,t-1}$	0.0091	-0.0157			0.0123	-0.0151	0.164**	0.1393**			0.1616**	0.142**
	(0.0123)	(0.0104)			(0.0122)	(0.0105)	(0.0548)	(0.0538)			(0.0549)	(0.0539)
$PR^{\tau,dw}_{i,t-1}$			-0.0216	-0.1096*	-0.0487	-0.108*			0.8232***	0.673**	0.7479***	0.6452**
			(0.0504)	(0.0427)	(0.0499)	(0.0429)			(0.2259)	(0.2231)	(0.2236)	(0.2227)
$Spill(A)^{\mu,up}_{i,t-1}$	0.112.	0.0492			0.1133.	0.0512	0.351	0.2512			0.3041	0.2015
	(0.0593)	(0.0499)			(0.059)	(0.05)	(0.2662)	(0.2599)			(0.2654)	(0.2591)
$Spill(A)^{\mu,dw}_{i,t-1}$	0.0292	-0.0184			0.0284	-0.0162	0.1676.	0.1421			0.1453	0.1259
	(0.0199)	(0.0168)			(0.0198)	(0.0168)	(0.0897)	(0.0874)			(0.0895)	(0.0872)
$Spill(A)^{\tau,up}_{i,t-1}$			-0.4933	-0.3114	-0.2876	-0.3668			4.67*	5.254**	5.391**	5.734**
			(0.4265)	(0.3548)	(0.4207)	(0.3562)			(1.91)	(1.855)	(1.885)	(1.847)
$Spill(A)^{\tau,dw}_{i,t-1}$			0.0024	0.0225	-0.0017	0.0232			0.222	0.1801	0.1863	0.14
			(0.0323)	(0.0269)	(0.0319)	(0.027)			(0.1444)	(0.1404)	(0.1429)	(0.14)
$W_{i,t-1}$		-0.002		-0.0052		-0.0025		0.0979		0.1411*		0.1022
		(0.0126)		(0.0116)		(0.0126)		(0.0651)		(0.0605)		(0.0647)
$(L^P/L)_{i,t-1}$		-0.3684*		-0.3788**		-0.3712*		0.867		1.237		1.062
		(0.1437)		(0.1442)		(0.1449)		(0.7488)		(0.7541)		(0.751)
$(E/L)_{i,t-1}$		0.0217.		0.0267*		0.0258*		0.1936**		0.1725**		0.1787**
		(0.0127)		(0.0127)		(0.0128)		(0.0634)		(0.0642)		(0.0637)
$(M/L)_{i,t-1}$		0.0221		0.0205		0.023		0.1395.		0.1526*		0.1206
		(0.015)		(0.0149)		(0.0151)		(0.0773)		(0.0767)		(0.0773)
$(W^P/W)_{i,t-1}$		0.3604***		0.3477***		0.3495***		-1.233**		-1.095*		-1.123*
		(0.0869)		(0.0869)		(0.0869)		(0.4468)		(0.4485)		(0.445)
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9393	0.9579	0.938	0.958	0.9406	0.9583	0.8849	0.892	0.8827	0.8916	0.8871	0.8939

Notes: The table shows the regression results of capital intensity $(K/L)_{i,t}$ and per-capital investment $(I/L)_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways weighted fixed-effects (FE) model. The weights used in the regressions are $A^{\mu}_{i,t}$ in the TFP regression and $L_{i,t}$ in all other regressions. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1.

Table SI.6: Effects on the share of production labor.

	Share of production labor						Relative wage for production labor					
	$\tau \to (L^P/L)_{i,t}$		$\mu \to (L^P/L)_{i,t}$		Both		$\tau \to (W^P/W)_{i,t}$		$\mu \to (W^P/W)_{i,t}$		Both	
	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(L^P/L)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$	$(W^P/W)_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$(L^P/L)_{i,t-1}$	0.499***	0.4891***	0.4871***	0.4796***	0.4854***	0.4863***		0.234***		0.2174***		0.2212***
	(0.0293)	(0.0333)	(0.0303)	(0.0335)	(0.0301)	(0.0335)		(0.0567)		(0.057)		(0.0573)
$(W^P/W)_{i,t-1}$		0.0557**		0.0537**		0.0539**	0.4499***	0.3903***	0.4467***	0.3894***	0.4417***	0.3884***
		(0.0198)		(0.0199)		(0.0199)	(0.033)	(0.0338)	(0.033)	(0.0339)	(0.0331)	(0.034)
$A^{\mu}_{i,t-1}$	-0.0225**	-0.0145.			-0.0201**	-0.0143.	-0.0249*	-0.0129			-0.0236*	-0.0139
	(0.0069)	(0.0078)			(0.0069)	(0.0078)	(0.0117)	(0.0134)			(0.0118)	(0.0134)
$A^{\tau}_{i,t-1}$			-0.0326.	-0.0235	-0.0322.	-0.0273			-0.0582*	-0.0163	-0.0544.	-0.0175
			(0.0174)	(0.0174)	(0.0174)	(0.0175)			(0.029)	(0.0296)	(0.0293)	(0.0299)
$PR^{\mu,up}_{i,t-1}$	0.0044	0.0039			0.0045	0.004	0.0062	0.0064			0.0071	0.0069
	(0.0033)	(0.0032)			(0.0033)	(0.0032)	(0.0056)	(0.0055)			(0.0056)	(0.0055)
$PR^{\mu,dw}_{i,t-1}$	-0.005*	-0.0031			-0.0051*	-0.0033	8e-04	-1e-04			-3e-04	-7e-04
	(0.0024)	(0.0024)			(0.0024)	(0.0024)	(0.0041)	(0.0041)			(0.0041)	(0.0041)
$PR^{\tau,dw}_{i,t-1}$			-0.0094	-0.0083	-0.0045	-0.0073			0.0014	0.0019	0.0025	0.0018
			(0.0099)	(0.0099)	(0.0099)	(0.0099)			(0.0167)	(0.0169)	(0.0169)	(0.017)
$Spill(A)^{\mu,up}_{i,t-1}$	-0.0064	-7e-04			-0.0055	-4e-04	0.0106	0.002			0.0106	0.0031
	(0.0117)	(0.0115)			(0.0117)	(0.0116)	(0.0199)	(0.0197)			(0.0199)	(0.0198)
$Spill(A)^{\mu,dw}_{i,t-1}$	-0.007.	-0.0044			-0.0064	-0.0042	0.0021	0.0023			0.002	0.0021
	(0.0039)	(0.0039)			(0.0039)	(0.0039)	(0.0067)	(0.0066)			(0.0067)	(0.0067)
$Spill(A)^{\tau,up}_{i,t-1}$			0.1114	0.1007	0.0741	0.082			-0.253.	-0.1876	-0.2779.	-0.1985
			(0.084)	(0.0823)	(0.0836)	(0.0825)			(0.1416)	(0.1402)	(0.1423)	(0.1409)
$Spill(A)^{\tau,dw}_{i,t-1}$			-0.0011	0.0016	-4e-04	0.0022			-0.0028	-0.0076	-0.0042	-0.0081
			(0.0063)	(0.0062)	(0.0063)	(0.0063)			(0.0107)	(0.0106)	(0.0108)	(0.0107)
$W_{i,t-1}$		-0.0012		-0.0032		-0.0013		-0.0047		-0.0061		-0.0048
		(0.0029)		(0.0027)		(0.0029)		(0.0049)		(0.0046)		(0.0049)
$(K/L)_{i,t-1}$		0.0061*		0.0067*		0.0072*		-0.0102.		-0.0107*		-0.01.
		(0.0031)		(0.0031)		(0.0031)		(0.0052)		(0.0053)		(0.0053)
$(I/L)_{i,t-1}$		-0.0071***		-0.0077***		-0.0072***		-0.0013		-0.0014		-0.0013
		(0.0017)		(0.0017)		(0.0018)		(0.003)		(0.003)		(0.003)
$(E/L)_{i,t-1}$		0.0053.		0.0058*		0.0058*		0.012*		0.0113*		0.0115*
		(0.0028)		(0.0028)		(0.0028)		(0.0048)		(0.0049)		(0.0049)
$(M/L)_{i,t-1}$		-0.0039		-0.0033		-0.0034		-3e-04		0.0016		7e-04
		(0.0034)		(0.0034)		(0.0035)		(0.0059)		(0.0058)		(0.0059)
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9311	0.9338	0.93	0.9337	0.9317	0.9343	0.778	0.7878	0.7791	0.7879	0.7803	0.7885

Notes: The table shows the regression results of the share of production labor $(L^P/L)_{i,t}$ and relative wages for production labor $(W^P/W)_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways weighted fixed-effects (FE) model. The weights used in the regressions are $A^{\mu}_{i,t}$ in the TFP regression and $L_{i,t}$ in all other regressions. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{i,t-1}$, $(E/L)_{i,t-1}$, $(M/L)_{i,t-1}$, $W^P_{i,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, and $Spill(A)^{\alpha,d}_{i,t}$ are scaled by division by their standard deviation to obtain comparable coefficients across the different network effects. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1.

SI.4. Sectoral patterns of innovation

SI.4.1. Map between 6-digit NAICS codes and industry groups

Table SI.7: Mapping of 6-digit NAICS industries into subsamples

NAICS	Description	Inno intensive	Big industry	Patent central	Market central (up)	Market central (down)	Pavitt sector
311111	Dog & Cat Food Mnfct	X				X	
311119	Other Animal Food		X			X	
311211	Flour Milling		X		X		
311212	Rice Milling						
311213	Malt Mnfct						
311222	Soybean Processing		X	X	X	X	
311225	Fats & Oils Refining		X		X	X	
311230	Breakfast Cereal Mnfct					X	
311311	Sugarcane Mills				X		
311313	Beet Sugar Mnfct				X		
311320	Chocolate from Cacao Beans						
311330	Confect from Purch Chocolate	X		X		X	
311340	Nonchocolate Confectionery	X		X		X	
311411	Frozen Fruit, Juice & Veg		X			X	
311412	Frozen Specialty Food	X				X	
311421	Fruit & Vegetable Canning		X			X	
311422	Specialty Canning					X	
311423	Dried & Dehydrated Food	X		X	X	X	
311511	Fluid Milk Mnfct	X	X	X	X	X	
311512	Creamery Butter Mnfct	X		X		X	
311513	Cheese Mnfct		X		X	X	
311514	Dry & Condensed Dairy		X		X	X	
311520	Ice Cream & Frozen Dessert		X			X	
311611	Animal Slaughter		X		X	X	
311612	Meat Proc from Carcasses	X	X	X	X	X	
311613	Meat Byproduct Processing		X		X	X	
311615	Poultry Processing	X	X	X	X	X	
311711	Seafood Canning						
311811	Retail Bakeries					X	
311812	Commercial Bakeries					X	
311821	Cookie & Cracker	X		X			
311822	Flour Mixes from Purch Flour	X		X			
311830	Tortilla Mnfct	X					
311911	Roasted Nuts & Peanut Butter						
311919	Other Snack Food Mnfct	X		X		X	
311920	Coffee & Tea Mnfct		X			X	
311930	Flavor Syrup & Concentrate		X		X		
311941	Mayo, Dressing & Sauce					X	
311942	Spice & Extract	X	X	X	X	X	
311991	Perishable Prepared Food						
311999	All Other Miscellaneous Food	X	X	X	X	X	

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Table SI.7: Mapping of 6-digit NAICS industries into subsamples

NAICS	Description	Inno intensive	Big industry	Patent central	Market central (up)	Market central (down)	Pavitt sector
312111	Soft Drink Mnfct	X		X		X	
312112	Bottled Water Mnfct	X	X		X	X	
312113	Ice Mnfct	X		X		X	Pro
312120	Breweries		X			X	
312130	Wineries		X	X	X	X	
312140	Distilleries		X			X	Sup
312210	Tobacco Stem & Redrying				X	X	
313111	Yarn Spinning Mills	X	X	X	X		
313221	Narrow Fabric Mills				X		
313230	Nonwoven Fabric Mills	X	X	X	X		
313241	Weft Knit Fabric Mills				X		
313320	Fabric Coating Mills	X		X	X		Pro
314110	Carpet & Rug Mills						
314121	Curtain & Drapery Mills						
314991	Rope, Cordage, & Twine Mills						
315111	Sheer Hosiery Mills					X	
315221	Men's Under- & Nightwear	X					
315231	Women's Lingerie & Nightwear						
315292	Fur & Leather Apparel						
315991	Hat, Cap, & Millinery	X		X			
316110	Leather & Hide Tann & Finish		X		X	X	Sup
316211	Rubber & Plastics Footwear	X		X		X	Sup
316991	Luggage Mnfct	X		X			Sup
316992	Women's Handbag & Purse	X				X	Sup
321113	Sawmills		X		X		Sup
321114	Wood Preservation		X		X	X	Sup
321211	Hardwood Veneer & Plywood		X		X		Sup
321212	Softwood Veneer & Plywood		X		X		Sup
321213	Engineered Wood Member						Sup
321214	Truss Mnfct						Sup
321911	Wood Window & Door		X	X			Sup
321912	Cut Stock & Resaw Lumber		X	X	X		Sup
321918	Millwork (including Flooring)		X		X		Sup
321920	Wood Container & Pallet		X		X		Sup
321991	Manufact & Mobile Home					X	Sup
321992	Prefabricated Wood Building		X			X	Sup
322110	Pulp Mills	X	X	X	X		Sup
322121	Paper (exc Newsprint) Mills	X	X	X	X	X	Pro, Sup
322122	Newsprint Mills		X		X	X	Sup
322130	Paperboard Mills		X	X	X	X	Sup
322211	Corrugated & Solid Fiber Box		X		X	X	Sup
322212	Folding Paperboard Box		X		X		Sup
322213	Setup Paperboard Box		X		X		Sup
322221	Coated Paper & Plastics Film	X	X	X	X		Pro, Sci, Sup
322231	Die-Cut & Paper Office Suppl					X	Sup
322291	Sanitary Paper Product	X	X	X		X	Sup
323110	Commercial Lithograph Print		X		X	X	Sup

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Table SI.7: Mapping of 6-digit NAICS industries into subsamples

NAICS	Description	Inno intensive	Big industry	Patent central	Market central (up)	Market central (down)	Pavitt sector
323113	Commercial Screen Printing		X		X	X	Sup
323117	Books Printing		X			X	Sup
324110	Petroleum Refineries		X	X	X	X	Sup
324121	Asphalt Paving Mixture & Block	X	X	X		X	Pro
324122	Asphalt Shle & Coat Materials		X				Pro
324199	Petroleum & Coal Products		X		X	X	Sup
325131	Inorganic Dye & Pigment		X		X		Sup
325191	Gum & Wood Chemical				X	X	Sup
325199	Basic Organic Chemical		X		X	X	Pro, Sup
325211	Plastics Material & Resin		X	X	X	X	Sup
325212	Synthetic Rubber Mnfct		X		X		Sup
325311	Nitrogenous Fertilizer		X	X	X		Sup
325320	Pesticide & Agric Chemical	X	X	X		X	Sup
325411	Medicinal & Botanical	X	X	X	X	X	Pro
325414	Biological Products		X		X	X	Pro
325510	Paint & Coating	X	X	X	X	X	Sup
325520	Adhesive Mnfct	X	X	X	X		Sup
325611	Soap & Other Detergent	X	X	X	X	X	Sup
325612	Polish & Other Sanitation	X		X	X	X	Sup
325613	Surface Active Agent		X		X		Sup
325910	Printing Ink Mnfct	X	X	X			Sup
325920	Explosives Mnfct	X		X	X		Sup
325991	Custom Compound of Resins		X		X		Sup
325992	Photo Film, Paper & Chem		X	X	X	X	Sup
325998	Misc Chem Products	X	X	X	X	X	Pro, Sup
326111	Plastics Bag Mnfct	X	X	X	X		Pro
326112	Plastics Packag Film & Sheet		X		X		Pro
326113	Unlamin Plastics Film & Sheet		X	X	X		Pro
326121	Unlamin Plastics Profiles		X		X		Pro
326122	Plastics Pipe & Pipe Fitting	X	X	X	X		Pro
326130	Lamin Plastics Plate & Shape	X	X	X	X		Pro
326140	Polystyrene Foam Product	X	X	X	X		Pro
326150	Urethane & Foam	X	X	X	X		Pro
326160	Plastics Bottle Mnfct		X		X		Pro
326191	Plastics Plumbing Fixture		X		X	X	Pro
326192	Resilient Floor Covering		X		X		Pro
326211	Tire (exc Retreading)	X	X	X			Pro
326212	Tire Retreading		X			X	Pro
326220	Rubber & Plastics Hoses		X		X		Pro
326291	Rubber for Mechanical Use	X		X	X		Pro
326299	All Other Rubber Product	X		X	X		Pro
327111	China Plumbing & Bathroom						Pro
327121	Brick & Structural Clay Tile						Pro
327211	Flat Glass Mnfct		X	X	X		Pro
327212	Pressed & Blown Glass	X	X	X	X		Pro
327213	Glass Container Mnfct		X		X		Pro

continue on the next page

Table SI.7: Mapping of 6-digit NAICS industries into subsamples

NAICS	Description	Inno intensive	Big industry	Patent central	Market central (up)	Market central (down)	Pavitt sector
327215	Glass Products (Purch Glass)		X	X	X		Pro
327310	Cement Mnfct	X	X	X	X		Pro
327320	Ready-Mix Concrete		X			X	Pro
327331	Concrete Block & Brick					X	Pro
327332	Concrete Pipe Mnfct					X	Pro
327390	Other Concrete Product	X	X	X		X	Pro
327410	Lime Mnfct	X		X	X		Pro
327420	Gypsum Product Mnfct	X		X	X		Pro
327910	Abrasive Product Mnfct	X		X	X		Pro
327991	Cut Stone & Stone Product						Pro
327992	Treated Mineral & Earth				X		Pro
327993	Mineral Wool Mnfct		X				Pro
327999	Misc Nonmetal Mineral Prod				X	X	Pro, Sci
331111	Iron & Steel Mills		X		X	X	Sci
331222	Steel Wire Drawing				X		Pro, Sci
331315	Aluminum Sheet, Plate & Foil		X		X		Sci
331411	Smelting & Refining of Copper		X		X	X	Sci
331421	Copper Roll, Draw & Extrud		X		X		Pro, Sci
331491	Nonferr Metal Roll & Extrud		X		X		Pro, Sci
331492	Alloy of Nonferr Metal	X		X	X		Sci
332115	Crown & Closure				X		Pro
332117	Powder Metallurgy Part	X		X	X		Pro
332211	Cutlery & Flatware	X		X			Pro
332212	Hand & Edge Tool	X	X	X	X	X	Pro, Sup
332311	Metal Build & Component		X			X	Pro
332313	Plate Work Mnfct		X		X		Pro, Sci, Sup
332321	Metal Window & Door		X	X			Pro
332322	Sheet Metal Work Mnfct	X	X	X	X		Pro
332323	Architect Metal Work		X			X	Pro
332410	Boiler & Heat Exchanger	X		X			Pro, Sup
332420	Metal Tank (Heavy Gauge)	X		X			Pro, Sup
332431	Metal Can Mnfct		X		X		Pro
332439	Other Metal Container		X		X		Pro
332510	Hardware Mnfct	X	X	X	X		Pro
332611	Spring (Heavy Gauge)						Pro
332618	Other Fabricated Wire Prod				X		Pro, Sci
332710	Machine Shops		X		X	X	Pro
332721	Precision Turned Product		X		X		Pro
332722	Bolt, Nut & Screw		X	X	X		Pro
332811	Metal Heat Treating	X	X	X	X		Pro
332812	Metal Coat, Engrav & Allied		X		X		Pro
332813	Electroplating & Polishing	X	X	X	X		Pro
332911	Industrial Valve Mnfct		X		X		Sup
332912	Fluid Power Valve & Hose Fitt		X		X	X	Sci, Sup
332913	Plumb Fixture Fitt & Trim						Pro, Sci, Sup
332919	Metal Valve & Pipe Fitting	X	X	X	X		Sci, Sup
332991	Ball & Roller Bearing	X	X	X	X		Sup

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Table SI.7: Mapping of 6-digit NAICS industries into subsamples

NAICS	Description	Inno intensive	Big industry	Patent central	Market central (up)	Market central (down)	Pavitt sector
332992	Small Arms Ammunition	X		X		X	Pro, Sup
332993	Ammunition (exc Small Arms)	X		X		X	Pro, Sup
332994	Small Arms Mnfct	X		X		X	Pro
332996	Fabricated Pipe & Pipe Fitting		X		X		Sci
333111	Farm Machinery & Equipment	X		X	X	X	Sup
333112	Lawn & Garden Tractor & Equ	X		X		X	Sci, Sup
333120	Construction Machinery		X	X		X	Pro, Sup
333131	Mining Machinery & Equ	X		X		X	Pro, Sci, Sup
333132	Oil & Gas Field Machinery					X	Sup
333210	Sawmill & Woodwork Machine	X					Sup
333220	Plastics & Rubber Machinery	X		X			Sup
333293	Printing Machinery & Equ	X		X			Sup
333294	Food Product Machinery	X		X			Sup
333295	Semiconductor Machinery				X	X	Sup
333311	Automatic Vending Machine	X		X		X	Sup
333314	Optical Instrument & Lens	X		X			Pro
333315	Photogr & Photocopy Equ	X		X		X	Pro, Sup
333414	Heat Equipment					X	Pro, Sup
333512	Machine Tool, Metal Cut	X		X			Sup
333514	Die Set, Jig & Fixture				X		Pro, Sup
333515	Cutting & Machine Tool	X	X	X	X		Pro, Sup
333516	Rolling Mill Machinery & Equ	X		X		X	Sup
333611	Turbine & Generator Units	X		X		X	Sup
333612	Speed Changer, Drive & Gear	X	X	X	X		Sup
333613	Power Transmission Equ	X	X	X	X		Sup
333618	Other Engine Equipment		X		X	X	Pro, Sci, Sup
333911	Pump & Pumping Equipment	X	X	X	X	X	Sup
333912	Air & Gas Compressor				X		Sup
333913	Measuring & Dispensing Pump	X				X	Sup
333921	Elevator & Moving Stairway	X				X	Sup
333922	Conveyor & Conveying Equ	X		X		X	Sup
333923	Overhead Crane & Monorail	X		X		X	Sci, Sup
333924	Truck, Tractor & Stacker	X		X			Sci, Sup
333991	Power-Driven Handtool	X		X			Sup
333992	Welding & Soldering Equ	X		X			Pro, Sup
333993	Packaging Machinery	X		X			Sup
334111	Electronic Computer	X	X	X	X	X	Pro
334112	Computer Storage Device	X		X		X	Pro
334113	Computer Terminal					X	Pro
334210	Telephone Apparatus	X	X	X		X	Pro
334220	Radio, TV, Wirel Communic	X	X	X	X	X	Pro, Sci
334310	Audio & Video Equipment		X		X	X	Pro
334411	Electron Tube Mnfct	X	X		X		Pro
334412	Bare Printed Circuit Board	X	X	X	X		Pro
334413	Semiconductor & Rel Device	X	X	X	X	X	Pro
334414	Electronic Capacitor		X		X		Pro
334417	Electronic Connector		X		X		Pro

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Table SI.7: Mapping of 6-digit NAICS industries into subsamples

NAICS	Description	Inno intensive	Big industry	Patent central	Market central (up)	Market central (down)	Pavitt sector
334418	Printed Circuit Assembly	X	X	X	X	X	Pro
334510	Electromedical & -therapeutic	X		X		X	Pro
334511	Search, Navig, Nautic System	X		X		X	Pro
334512	Env Ctrl for Resident Use	X		X			Pro
334513	Instr for Control Process	X		X	X		Pro
334514	Fluid Meter & Count Device	X					Pro
334515	Measure & Test Elctr Signals				X		Pro
334517	Irradiation Apparatus	X		X			Pro
334518	Watch, Clock, & Part	X	X	X	X		Pro
334611	Software Reproducing	X		X			Sup
334613	Magnetic & Optic Recording	X		X		X	Pro
335110	Electric Lamp Bulb & Part	X		X			Pro
335129	Other Lighting Equipment						Pro
335211	Elctr Housewares & Home Fan						Pro
335221	Household Cooking Appliance	X					Pro
335222	Refrigerator & Freezer	X					Pro
335224	Household Laundry Equ	X				X	Pro
335228	Major Household Appliance						Pro
335311	Power, Distr & Transformer	X		X	X		Pro
335312	Motor & Generator	X	X	X	X	X	Pro
335313	Switchgear & Switchboard		X	X	X		Pro
335314	Relay & Industrial Control		X		X	X	Pro
335911	Storage Battery Mnfct	X		X			Pro
335912	Primary Battery Mnfct	X					Pro
335921	Fiber Optic Cable		X		X		Pro
335929	Communic & Energy Wire		X		X		Pro
335931	Current-Carrying Wire Device	X	X	X			Pro
335932	Noncurrent-Carry Wir Device	X	X	X			Pro
335991	Carbon & Graphite Product	X		X	X		Pro
335999	Miscellaneous Electrical Equ	X		X		X	Pro
336111	Automobile Mnfct	X		X	X	X	Pro
336112	Light Truck & Utility Vehicle					X	Pro
336120	Heavy Duty Truck Mnfct					X	Pro
336211	Motor Vehicle Body		X	X		X	Pro, Sup
336212	Truck Trailer Mnfct	X				X	Pro
336213	Motor Home Mnfct	X				X	Pro
336214	Travel Trailer & Camper	X				X	Pro
336311	Carburetor, Piston & Valve		X		X		Sup
336321	Vehicular Lighting Equipment		X	X		X	Pro
336330	Vhcl Steer & Suspension Parts		X	X		X	Pro, Sup
336340	Motor Vehicle Brake System		X	X	X	X	Pro, Sup
336350	Vhcl Power Train Parts		X	X	X	X	Pro
336360	Vhcl Seat & Interior		X		X	X	Pro, Sci
336391	Motor Vhcl Air-Conditioning		X		X	X	Sup
336411	Aircraft Mnfct	X	X	X	X	X	Sci
336412	Aircraft Engine & Parts		X		X	X	Sci, Sup
336413	Other Aircraft Parts & Aux		X			X	Sci

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Table SI.7: Mapping of 6-digit NAICS industries into subsamples

NAICS	Description	Inno intensive	Big industry	Patent central	Market central (up)	Market central (down)	Pavitt sector
336414	Guided Missile & Space Vhcl	X		X		X	Sci
336415	Missile & Space Vhcl Propuls					X	Sci
336419	Missile & Space Vhcl Parts	X				X	Sci
336510	Railroad Rolling Stock	X	X	X		X	Pro, Sci
336611	Ship Building & Repairing	X		X		X	Sci
336612	Boat Building	X		X		X	Sci
336991	Motorcycle, Bicycle, & Parts	X		X		X	Sci
336999	Transportation Equipment	X		X		X	Pro, Sci
337110	Wood Kitchen Cabinet		X				Pro
337121	Upholstered Household Furnit					X	Pro
337122	Nonupholst Wood Furnit	X		X			Pro
337124	Metal Household Furniture	X					Pro
337125	Other Home Furniture	X		X			Pro
337211	Wood Office Furniture					X	Pro
337214	Office Furniture (exc Wood)	X		X		X	Pro
337215	Showcase, Shelv & Locker		X	X	X	X	Pro, Sup
337910	Mattress Mnfct	X		X			Pro
337920	Blind & Shade Mnfct	X				X	Pro, Sup
339111	Laboratory & Furniture	X		X		X	
339112	Surgical & Medical Instrument	X	X	X	X	X	Sci
339113	Surgical Appliance & Supplies		X		X	X	Pro, Sci, Sup
339114	Dental Equipment & Supplies	X		X		X	Sci
339911	Jewelry (exc Costume)	X		X	X		Sci
339920	Sporting & Athletic Goods	X		X	X	X	Pro, Sci, Sup
339931	Doll & Stuffed Toy					X	Sci
339941	Pen & Mechanical Pencil	X					Sci
339950	Sign Mnfct	X		X		X	Pro, Sup
339992	Musical Instrument	X		X		X	Sci
339993	Fastener, Button, & Pin	X		X			Pro, Sic, Sup
339994	Broom, Brush, & Mop	X		X			Sci
339995	Burial Casket Mnfct	X		X		X	Sci
339999	All Other Miscellaneous	X		X		X	Pro, Sci, Sup

Notes: This table shows industries are subset into different groups to search for sectoral patterns of innovation. Innovation-intensive is measures as number of citation-weighted patents divided by output (A^{τ}/A^{μ}). Big industry are industries with above median industry size (A^{μ}). High patent centrality is given i has above median patent PageRank (up- & downwards) $PR^{\tau,dw}$. High up- and downstream market centrality are given i has above median upstream (downstream) PageRank $PR^{\mu,d}$. Pavitt sectors are identified using the classification proposed by (Bogliacino and Pianta, 2016). The codes are: Pro for production intensive, Sci for Sciene based, Sup for Suppliers dominated. Note that the Pavitt codes are not available for a larger subset of industries belonging to Food processing.

SI.4.2. By 2-digit sector

SI.4.2.1. Food processing

Table SI.8: Demand-pull and technology-push effects in Food processing sectors

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.6983***	0.4968***	0.0306	0.0349	0.5831***	0.2226			0.6827***	0.3424*	0.067	0.0076
	(0.0767)	(0.0947)	(0.0391)	(0.0341)	(0.0916)	(0.165)			(0.1287)	(0.1434)	(0.0473)	(0.0286)
$A^{\tau}_{i,t-1}$	-0.3206	-0.1575	1.001***	0.9874***			0.9008***	0.952***	-0.328	-0.2812	0.9385***	0.9731***
	(0.2463)	(0.2534)	(0.0256)	(0.0328)			(0.1162)	(0.1207)	(0.2739)	(0.2626)	(0.1018)	(0.1088)
$PR^{\mu,up}_{i,t-1}$			0.0074	0.0108	-0.0592.	0.0114			-0.0897.	0.0026	0.003	0.0138
			(0.0114)	(0.0115)	(0.0329)	(0.0519)			(0.0486)	(0.0524)	(0.013)	(0.0123)
$PR^{\mu,dw}_{i,t-1}$			0.0041	0.0126	0.0578	0.0944.			0.0414	0.0759	0.0131	0.0218*
			(0.0069)	(0.0094)	(0.0357)	(0.0531)			(0.0401)	(0.0479)	(0.0118)	(0.0105)
$PR^{\tau,dw}_{i,t-1}$	0.278	0.0677					0.1238	0.0626	0.2774	0.1359	0.1049.	0.0467
	(0.1928)	(0.1103)					(0.0798)	(0.0502)	(0.1896)	(0.1282)	(0.0633)	(0.0406)
$Spill(A)^{\mu,up}_{i,t-1}$			0.0016	-0.0117	0.0229	0.07			-0.0281	0.0401	-0.0068	-0.0076
			(0.0243)	(0.0221)	(0.0582)	(0.0804)			(0.0635)	(0.0804)	(0.0222)	(0.0228)
$Spill(A)^{\mu,dw}_{i,t-1}$			-0.0077	-0.0095	0.1061.	0.1254			0.0486	0.082	0.0107	0.0235
			(0.0144)	(0.0159)	(0.0617)	(0.0831)			(0.0679)	(0.0671)	(0.0169)	(0.0167)
$Spill(A)^{\tau,up}_{i,t-1}$	7.858**	2.557					2.074*	0.5733	8.253**	3.865*	1.495.	0.2625
	(2.687)	(2.012)					(0.8828)	(0.8041)	(2.745)	(1.879)	(0.7975)	(0.5631)
$Spill(A)^{\tau,dw}_{i,t-1}$	0.1373	0.0379					0.0174	-0.004	0.1358	0.0966	-0.0094	-0.0198
	(0.1318)	(0.1307)					(0.052)	(0.0522)	(0.1447)	(0.1138)	(0.0441)	(0.0402)
AR(1)	0	0	7e-04	4e-04	0	2e-04	8e-04	0.0012	0	0	5e-04	5e-04
AR(2)	0.863	0.9389	0.7458	0.7474	0.6879	0.7258	0.6942	0.9831	0.482	0.9749	0.8636	0.8884
Sargan	2e-04	6e-04	0.0204	0.0152	0	0.0108	0.0118	1e-04	0.0037	0.0018	0.0016	3e-04
Method	1-step-BB	1-step-BB	1-step-BB	1-step-BB	1-step-BB	1-step-BB	1-step-BB	1-step-BB	1-step-BB	1-step-BB	1-step-BB	1-step-BB
Controls		Y		Y		Y		Y		Y		Y
R^2	0.899	0.9286	0.9949	0.9944	0.9398	0.9168	0.9914	0.9942	0.8947	0.9253	0.9925	0.9937

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of Food processing industries (NAICS 2-digit code 31).

SI.4.2.2. Non-Metallic Manufacturing

Table SI.9: Demand-pull and technology-push effects in Non-Metallic manufacturing

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5975***	0.6909***	0.0484	0.0265	0.5302***	0.5572***			0.4645***	0.5605***	0.0346	0.0327
	(0.0984)	(0.0932)	(0.0487)	(0.0507)	(0.117)	(0.0939)			(0.1369)	(0.097)	(0.0621)	(0.0618)
$A^{\tau}_{i,t-1}$	0.0394	0.0849	0.994***	0.9792***			1.001***	0.8991***	0.0425	0.0981	1.027***	0.9157***
	(0.1719)	(0.2901)	(0.0448)	(0.0476)			(0.1572)	(0.119)	(0.181)	(0.2866)	(0.1462)	(0.1133)
$PR^{\mu,up}_{i,t-1}$			-0.012	-0.0125	-0.0158	-0.0393			-0.0017	-0.0288	-0.0037	-0.0084
			(0.0094)	(0.0112)	(0.0219)	(0.0302)			(0.024)	(0.0301)	(0.0102)	(0.0124)
$PR^{\mu,dw}_{i,t-1}$			-0.0127	-0.0097	0.0178	-0.0377			0.022	-0.0456	-0.0055	-0.0078
			(0.0101)	(0.0129)	(0.0153)	(0.0379)			(0.0188)	(0.0411)	(0.0114)	(0.0136)
$PR^{\tau,dw}_{i,t-1}$	0.0785	0.0581					0.0407	0.0661*	0.1064	0.0759	0.0294	0.0568.
	(0.0658)	(0.1042)					(0.0452)	(0.0319)	(0.0783)	(0.0991)	(0.0445)	(0.0292)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0041	-0.0062	-0.0011	0.026			0.0056	0.0186	-0.0221	-0.0229
			(0.0166)	(0.0158)	(0.0331)	(0.0544)			(0.0351)	(0.0618)	(0.0187)	(0.0176)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0123	0.0095	0.0391	0.0274			0.0372	0.025	-0.0053	-0.0058
			(0.0137)	(0.0132)	(0.0296)	(0.0395)			(0.0334)	(0.0429)	(0.0124)	(0.0137)
$Spill(A)^{\tau,up}_{i,t-1}$	-0.8038	1.117					1.74***	1.664**	-2.134	-0.3491	1.497***	1.505**
	(1.74)	(2.153)					(0.5085)	(0.5743)	(1.708)	(2.226)	(0.4398)	(0.4709)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0462	-0.0767					-0.0512	-0.0153	-0.0767	-0.1187	-0.0513	-0.0175
	(0.0707)	(0.086)					(0.0373)	(0.0353)	(0.0661)	(0.0904)	(0.0351)	(0.0355)
AR(1)		1e-04	0.0015	0.0014		0	1e-04	0.0063	0	1e-04	0.0022	0.0078
AR(2)	0.1328	0.345	0.2525	0.0664	0.1232	0.5513	0.6786	0.8131	0.2108	0.7652	0.9401	0.9263
Sargan	0.0016	0.002	0.0014	1e-04	0	1e-04	0.0013	0.0088	0	1e-04	0.0016	0.0041
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9696	0.9462	0.9966	0.9964	0.9716	0.9483	0.9957	0.9952	0.9679	0.946	0.9961	0.9955

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of NonMetal industries (NAICS 2-digt code 32).

SI.4.2.3. Metallic and Machinery manufacturing

Table SI.10: Demand-pull and technology-push effects in Metallic and Machinery manufacturing

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5624***	0.4186***	0.0137	0.0061	0.78***	0.7392***			0.7071***	0.6474***	0.0367.	-0.0015
	(0.0373)	(0.059)	(0.0196)	(0.0188)	(0.0689)	(0.0867)			(0.0903)	(0.0985)	(0.02)	(0.0159)
$A^{\tau}_{i,t-1}$	0.2357	0.292	1.084***	1.089***			1.254***	1.182***	0.3616	0.1782	1.246***	1.166***
	(0.2149)	(0.2619)	(0.0191)	(0.0271)			(0.1009)	(0.0802)	(0.3341)	(0.3139)	(0.09)	(0.0776)
$PR^{\mu,up}_{i,t-1}$			-0.008	-0.0039	-0.0464.	-0.0326			-0.0202	-0.0447	-0.0091	-0.008
			(0.007)	(0.0081)	(0.027)	(0.0265)			(0.028)	(0.031)	(0.0076)	(0.0074)
$PR^{\mu,dw}_{i,t-1}$			0.0124*	0.0098.	-0.0193	0.0021			-0.0308	-0.0108	0.0081	0.0059
			(0.005)	(0.0056)	(0.0277)	(0.0252)			(0.0283)	(0.0252)	(0.0055)	(0.0048)
$PR^{\tau,dw}_{i,t-1}$	0.0222	0.0507					-0.0458	-0.025	0.0539	0.0986	-0.0552	-0.0189
	(0.09)	(0.1007)					(0.0421)	(0.0257)	(0.15)	(0.1077)	(0.0351)	(0.0258)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0221*	-0.0106	0.0852**	0.0859**			0.098**	0.0741.	-0.0155	-0.0091
			(0.009)	(0.01)	(0.0286)	(0.031)			(0.033)	(0.0392)	(0.0102)	(0.0099)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0109	0.0103	-0.1085**	-0.0809*			-0.1389***	-0.096**	0.0023	0.0126.
			(0.0067)	(0.0075)	(0.0338)	(0.0329)			(0.0387)	(0.0344)	(0.0067)	(0.0074)
$Spill(A)^{\tau,up}_{i,t-1}$	2.052	6.663***					0.7965	0.3382	7.514***	8.97***	0.629	0.2332
	(1.428)	(1.887)					(0.757)	(0.6235)	(1.757)	(2.051)	(0.6482)	(0.5991)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.1443*	-0.246*					-0.0858***	-0.0683**	-0.2378*	-0.2365*	-0.0738**	-0.0615**
	(0.0678)	(0.0988)					(0.0224)	(0.0229)	(0.0963)	(0.1073)	(0.0233)	(0.0224)
AR(1)	0	0	0.0269	0.0228	0	0	0.0461	0.0104	0	0	0.006	0.0079
AR(2)	0.4529	0.3061	0.5856	0.5822	0.6946	0.8913	0.3849	0.3743	0.5486	0.4561	0.3931	0.397
Sargan	0	0	0	0.0029	0	0	0	0	0	0	0	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9209	0.8912	0.9957	0.9953	0.9157	0.9124	0.9953	0.9959	0.8972	0.8837	0.9953	0.9959

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of Metal industries (NAICS 2-digit code 33).

SI.4.3. Innovation intensity

SI.4.3.1. Sectors with a high innovation-intensity

Table SI.11: Demand-pull and technology-push effects on Innovation-intensive industries

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5394***	0.5587***	0.0162	0.013	0.6693***	0.7179***			0.5774***	0.7***	0.0068	0.0026
	(0.04)	(0.0416)	(0.0144)	(0.0146)	(0.0669)	(0.0761)			(0.0784)	(0.0715)	(0.0161)	(0.0162)
$A^{\tau}_{i,t-1}$	0.168	-0.2289	1.083***	1.091***			1.225***	1.232***	4e-04	-0.3227	1.266***	1.252***
	(0.243)	(0.335)	(0.0153)	(0.0265)			(0.0702)	(0.0615)	(0.3609)	(0.3554)	(0.0521)	(0.0504)
$PR^{\mu,up}_{i,t-1}$			-0.0014	-0.0028	-0.0245	-0.0202			0.0159	0.0078	-0.0014	-0.0027
			(0.0041)	(0.0047)	(0.0224)	(0.0224)			(0.0295)	(0.0307)	(0.0041)	(0.0039)
$PR^{\mu,dw}_{i,t-1}$			0.0066	0.0034	0.0384	0.0413			0.0775.	0.0886*	0.0024	-4e-04
			(0.0042)	(0.005)	(0.0352)	(0.0323)			(0.0398)	(0.0356)	(0.0045)	(0.0045)
$PR^{\tau,dw}_{i,t-1}$	0.0854	0.2832*					-0.008	-0.0134	0.1759	0.2504*	-0.0331.	-0.0287*
	(0.1446)	(0.1117)					(0.0275)	(0.0213)	(0.1574)	(0.1062)	(0.0197)	(0.0146)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0191**	-0.0125.	0.0494.	0.0477			-0.0156	-0.0259	-0.0059	-0.0051
			(0.0062)	(0.0066)	(0.0283)	(0.0332)			(0.0333)	(0.0396)	(0.0055)	(0.0057)
$Spill(A)^{\mu,dw}_{i,t-1}$			-5e-04	3e-04	-0.0322	-0.0239			-0.0949**	-0.0871*	0.0056	0.0047
			(0.0048)	(0.0055)	(0.031)	(0.0325)			(0.0325)	(0.0349)	(0.0048)	(0.0048)
$Spill(A)^{\tau,up}_{i,t-1}$	3.881*	4.756*					1.78***	1.367***	9.629***	8.218***	1.481***	1.161***
	(1.583)	(2.019)					(0.384)	(0.3329)	(2.014)	(2.122)	(0.3058)	(0.277)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0639	0.0259					-0.1079***	-0.094***	-0.0014	0.1792	-0.1092***	-0.1003***
	(0.1313)	(0.1377)					(0.0207)	(0.0206)	(0.1585)	(0.1504)	(0.0183)	(0.0217)
AR(1)	0	0	0	0	0	0	0	0	0	0	0	0
AR(2)	0.9054	0.9888	0.044	0.0938	0.9755	0.8194	0.0434	0.0567	0.8279	0.9325	0.0511	0.0589
Sargan	0	0	0	0.0016	0	0	0	0.0017	0	0	0	1e-04
Controls		Y		Y		Y		Y		Y		Y
R^2	0.916	0.8813	0.9984	0.998	0.9181	0.9078	0.9977	0.998	0.8858	0.8791	0.9982	0.9984

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of innovation-intensive industries defined by an above median innovation intensity (A^{τ}_{i}/A^{μ}_{i}).

SI.4.3.2. Sectors with a low innovation-intensity

Table SI.12: Demand-pull and technology-push effects in Non-Innovation-intensive industries

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5031***	0.4837***	0.0272	-0.0056	0.7667***	0.7255***			0.6917***	0.7095***	0.0506	-7e-04
	(0.0517)	(0.0609)	(0.0379)	(0.042)	(0.0981)	(0.0996)			(0.1026)	(0.102)	(0.0463)	(0.0457)
$A^{\tau}_{i,t-1}$	0.2706*	0.3198.	1.038***	1.021***			1.186***	1.067***	0.1219	0.1821	1.184***	1.098***
	(0.1294)	(0.1677)	(0.0313)	(0.0341)			(0.0864)	(0.0689)	(0.1186)	(0.1288)	(0.0793)	(0.0577)
$PR^{\mu,up}_{i,t-1}$			0.0038	0.0048	-0.0732***	-0.0752***			-0.069**	-0.0684**	3e-04	0.0033
			(0.0095)	(0.0099)	(0.0216)	(0.0198)			(0.0231)	(0.0234)	(0.0108)	(0.0099)
$PR^{\mu,dw}_{i,t-1}$			0.003	0.0054	-0.0341.	-0.0416*			-0.0389*	-0.0243	0.0056	0.0067
			(0.006)	(0.0087)	(0.0186)	(0.0188)			(0.0185)	(0.0226)	(0.0074)	(0.0094)
$PR^{\tau,dw}_{i,t-1}$	0.0542	0.2297					-0.1774.	0.0513	0.4148*	0.4726**	-0.1828.	0.0132
	(0.1453)	(0.1895)					(0.1071)	(0.0713)	(0.1701)	(0.1777)	(0.0941)	(0.0641)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0156	-0.0052	0.0922**	0.0979**			0.0717*	0.0506	-0.0225	-0.009
			(0.0129)	(0.0145)	(0.0318)	(0.0298)			(0.0311)	(0.0331)	(0.0142)	(0.0159)
$Spill(A)^{\mu,dw}_{i,t-1}$			-0.0033	0.0105	-0.0566	-0.0359			-0.0784	-0.071	-0.0086	0.0075
			(0.0116)	(0.0114)	(0.0518)	(0.0433)			(0.0509)	(0.0487)	(0.0126)	(0.0113)
$Spill(A)^{\tau,up}_{i,t-1}$	2.748.	4.546*					2.408***	0.4972	1.289	3.197.	2.078***	0.8024.
	(1.47)	(1.92)					(0.6854)	(0.7851)	(1.564)	(1.724)	(0.5743)	(0.4467)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0611	-0.0415					-0.0322	-0.0538*	-0.1134.	-0.0983	-0.0357	-0.0475*
	(0.0574)	(0.0679)					(0.0303)	(0.0224)	(0.0591)	(0.0625)	(0.029)	(0.0216)
AR(1)	0	0	0.0011	0.0022		0	2e-04	0.0031		0	9e-04	0.0029
AR(2)	0.9332	0.7449	0.6352	0.6589	0.9511	0.9555	0.2423	0.5757	0.9243	0.9263	0.3571	0.496
Sargan	0	4e-04	1e-04	0.0066	0	0	0	0	0	0	0	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9525	0.9232	0.9905	0.9898	0.9491	0.9533	0.9852	0.9879	0.9472	0.9335	0.9859	0.9892

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of innovation-intensive industries defined by a below median innovation intensity $(A^{\tau}_{i}/A^{\mu}_{i})$.

SI.4.4. Market size

SI.4.4.1. Big industries

Table SI.13: Demand-pull and technology-push effects in Big industries

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5116***	0.4838***	-0.0423	-0.0686.	0.5763***	0.5674***			0.3642*	0.5871***	-0.0245	-0.0573
	(0.0619)	(0.0662)	(0.033)	(0.041)	(0.1439)	(0.0975)			(0.1828)	(0.1029)	(0.0442)	(0.0379)
$A^{\tau}_{i,t-1}$	0.1732	0.0343	1.058***	1.041***			1.11***	1.144***	-0.1267	0.0988	1.14***	1.15***
	(0.1068)	(0.0975)	(0.0164)	(0.021)			(0.1072)	(0.0682)	(0.201)	(0.1008)	(0.0829)	(0.0635)
$PR^{\mu,up}_{i,t-1}$			0.0133.	0.0106	-0.0287	-0.0361*			-0.0029	-0.0319.	0.0088	0.0062
			(0.0073)	(0.0069)	(0.0215)	(0.018)			(0.03)	(0.0183)	(0.0067)	(0.0064)
$PR^{\mu,dw}_{i,t-1}$			0.0136***	0.0103*	0.0061	-0.0069			0.0189	0.0026	0.0092.	0.0096.
			(0.0038)	(0.005)	(0.0173)	(0.0149)			(0.027)	(0.0159)	(0.0048)	(0.0056)
$PR^{\tau,dw}_{i,t-1}$	0.0077	0.0452					0.0491	-0.0061	0.254.	0.0673	0.0277	-0.0013
	(0.0604)	(0.0617)					(0.0525)	(0.0278)	(0.1462)	(0.0448)	(0.0381)	(0.0262)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0062	0.0056	0.0205	0.035			0.0102	0.0026	-0.0146	-0.0034
			(0.012)	(0.0126)	(0.0245)	(0.0259)			(0.0319)	(0.0268)	(0.0127)	(0.0128)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0086	0.0177.	-0.0291	-0.0258			-0.0274	-0.042	4e-04	0.0132
			(0.0074)	(0.0099)	(0.0223)	(0.0238)			(0.0249)	(0.0258)	(0.0079)	(0.009)
$Spill(A)^{\tau,up}_{i,t-1}$	-1.422	-0.3816					1.308**	0.8623**	-0.1246	0.9263	1.116**	0.7302*
	(0.9352)	(1.095)					(0.4987)	(0.3337)	(1.273)	(0.9836)	(0.3849)	(0.3005)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.1058*	-0.0611					-0.0896**	-0.0703**	-0.137.	-0.1369**	-0.09***	-0.0756***
	(0.0436)	(0.0515)					(0.0275)	(0.024)	(0.073)	(0.0448)	(0.0246)	(0.0218)
AR(1)	0	0	0	0	0	0	0.0029	0	0	0	0.0011	0
AR(2)	0.0196	0.024	0.0618	0.0387	0.0209	0.006	0.1697	0.0776	0.0228	0.0064	0.1741	0.1719
Sargan	1e-04	0	0.0233	0.1511	0	0	0	1e-04	0	0	0	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9772	0.9725	0.9966	0.9961	0.9768	0.977	0.9949	0.996	0.9602	0.9737	0.9956	0.9961

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of big industries defined by an above median industry size (A^{μ}_{i}).

SI.4.4.2. Small industries

Table SI.14: Demand-pull and technology-push effects in Small industries

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5073***	0.5413***	0.0229	0.02	0.7057***	0.6489***			0.579***	0.6246***	0.0158	-2e-04
	(0.047)	(0.042)	(0.0186)	(0.0199)	(0.0571)	(0.0636)			(0.0774)	(0.0705)	(0.0215)	(0.0206)
$A^{\tau}_{i,t-1}$	0.0663	-0.0403	1.058***	1.042***			1.087***	1.102***	0.139	0.0084	1.126***	1.104***
	(0.3422)	(0.2197)	(0.0225)	(0.0221)			(0.1147)	(0.0707)	(0.4305)	(0.2617)	(0.0914)	(0.0544)
$PR^{\mu,up}_{i,t-1}$			-9e-04	1e-04	-0.0564**	-0.0548**			-0.0206	-0.0384.	0.0017	0.001
			(0.0081)	(0.009)	(0.0204)	(0.0197)			(0.0283)	(0.023)	(0.009)	(0.009)
$PR^{\mu,dw}_{i,t-1}$			0.0039	0.0024	0.0322	0.0065			0.0731*	0.0357	0.0056	0.0027
			(0.0059)	(0.0069)	(0.0351)	(0.0272)			(0.0371)	(0.0278)	(0.0068)	(0.0065)
$PR^{\tau,dw}_{i,t-1}$	0.1173	0.0977					0.033	0.0158	0.0895	0.07	0.0083	0.0093
	(0.1602)	(0.099)					(0.0518)	(0.0362)	(0.1947)	(0.1187)	(0.0377)	(0.0248)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0161	-0.0166	0.0177	0.0184			-0.0082	-0.0046	-0.0163	-0.0138
			(0.0103)	(0.0105)	(0.0272)	(0.0303)			(0.0333)	(0.0342)	(0.0102)	(0.0105)
$Spill(A)^{\mu,dw}_{i,t-1}$			-0.0017	-0.0023	-0.0837**	-0.0769*			-0.0923*	-0.0756*	-0.0038	0.0051
			(0.0085)	(0.0083)	(0.0314)	(0.0315)			(0.0439)	(0.0357)	(0.0086)	(0.0085)
$Spill(A)^{\tau,up}_{i,t-1}$	7.469***	5.942**					1.95**	0.9831	9.633***	7.002**	1.542**	0.7435
	(1.958)	(2.071)					(0.7049)	(0.7466)	(2.243)	(2.169)	(0.5678)	(0.598)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0316	-0.0357					-0.0486	-0.0553**	-0.0288	-0.0259	-0.0547*	-0.0554**
	(0.0935)	(0.0722)					(0.0321)	(0.0211)	(0.111)	(0.0754)	(0.0272)	(0.0188)
AR(1)		0	0.0071	0.0056	0	0	0.0846	0.0059		0	0.0308	0.0048
AR(2)	0.9893	0.9727	0.498	0.4887	0.6033	0.5663	0.5482	0.3716	0.9214	0.7744	0.4707	0.3657
Sargan	1e-04	0	1e-04	2e-04	0	0	0	0	0	0	0	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.8655	0.8842	0.9948	0.9948	0.895	0.8986	0.9929	0.9944	0.8424	0.8825	0.9937	0.9947

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of small industries defined by a below median industry size (A^{μ}_{i}).

SI.4.5. Pavitt sector groups

SI.4.5.1. Science-based sectors

Table SI.15: Demand-pull and technology-push effects in Science-based sectors.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5287***	0.5553***	0.053	0.0225	0.5106***	0.6433***			0.5957***	0.642***	0.0645	0.0443
	(0.0779)	(0.1083)	(0.0556)	(0.0426)	(0.1507)	(0.1207)			(0.179)	(0.1725)	(0.0686)	(0.0391)
$A^{\tau}_{i,t-1}$	0.2759	0.3663	1.075***	1.06***			1.257***	1.286***	0.0637	0.3612	1.31***	1.246***
	(0.3643)	(0.3226)	(0.0247)	(0.047)			(0.1724)	(0.1029)	(0.5151)	(0.3592)	(0.0984)	(0.0958)
$PR^{\mu,up}_{i,t-1}$			-0.0158	-0.0119	0.0372	-0.0177			0.0304	0.0046	-0.0093	-0.0109
			(0.0107)	(0.0102)	(0.0413)	(0.0353)			(0.0512)	(0.038)	(0.012)	(0.0088)
$PR^{\mu,dw}_{i,t-1}$			0.0018	5e-04	0.0249	0.0103			-0.0159	-0.0275	-0.0059	-0.0039
			(0.0059)	(0.0065)	(0.025)	(0.0213)			(0.0319)	(0.0266)	(0.0061)	(0.0065)
$PR^{\tau,dw}_{i,t-1}$	-0.0979	-0.0828					0.0176	-0.0351	0.2431	0.0572	-0.0447	-0.0311
	(0.1809)	(0.1125)					(0.0882)	(0.0371)	(0.1901)	(0.1389)	(0.0548)	(0.0352)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0186	-0.0144	0.0923*	0.0346			0.1221*	0.0872	-0.0052	-0.0016
			(0.0144)	(0.0163)	(0.0459)	(0.0555)			(0.0591)	(0.0574)	(0.0133)	(0.0137)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0116	0.0138	-0.0604	-0.0571			-0.0918	-0.0988.	0.0024	0.0101
			(0.0164)	(0.0159)	(0.0557)	(0.0397)			(0.064)	(0.0525)	(0.0173)	(0.0135)
$Spill(A)^{\tau,up}_{i,t-1}$	-4.111	1.601					3.041.	1.394	6.506.	5.908.	1.533*	1.121
	(3.27)	(3.121)					(1.686)	(0.9076)	(3.857)	(3.244)	(0.7209)	(0.7515)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.177.	-0.0704					-0.1148*	-0.1419***	-0.2484	-0.3146*	-0.1134***	-0.1316***
	(0.1058)	(0.1073)					(0.0452)	(0.0297)	(0.1984)	(0.1255)	(0.0242)	(0.035)
AR(1)	7e-04	0.0048	0.0225	0.004	0	0		0.0015	0	1e-04		
AR(2)	0.8111	0.8123	0.0335	0.0074	0.8336	0.5772	0.5283	0.4236	0.8311	0.9539	0.1171	0.2701
Sargan	0.0024	0.0016	0.0155	0.0552	4e-04	0.0012	0.0015	5e-04	0.002	0.0018	0.0012	0.0019
Controls		Y		Y		Y		Y		Y		Y
R^2	0.942	0.9467	0.9974	0.9969	0.9555	0.958	0.9945	0.9964	0.9304	0.9472	0.9969	0.9969

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of Science-based industries (see (Bogliacino and Pianta, 2016)).

SI.4.5.2. Suppliers-dominated sectors

Table SI.16: Demand-pull and technology-push effects in Supplier dominated sectors.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.6488***	0.6351***	0.0571*	0.0453*	0.8444***	0.8141***			0.6259***	0.6898***	0.0431	0.0065
	(0.0514)	(0.0676)	(0.0256)	(0.0224)	(0.0744)	(0.0882)			(0.0936)	(0.0942)	(0.0303)	(0.0253)
$A^{\tau}_{i,t-1}$	-0.4345	0.0346	1.044***	1.054***			1.187***	1.144***	-0.2396	-0.0629	1.208***	1.155***
	(0.3649)	(0.3119)	(0.02)	(0.0295)			(0.0809)	(0.0643)	(0.3478)	(0.3406)	(0.0743)	(0.0705)
$PR^{\mu,up}_{i,t-1}$			-0.013	-0.0127.	-0.0112	-0.0362			0.0398	0.0144	-0.0063	-0.0061
			(0.0086)	(0.0075)	(0.0278)	(0.0268)			(0.0368)	(0.0325)	(0.0082)	(0.0072)
$PR^{\mu,dw}_{i,t-1}$			-0.0078	-0.0075	-0.0079	-0.0515.			0.0323	0.01	-0.0028	-0.0023
			(0.0062)	(0.0068)	(0.0199)	(0.0308)			(0.0298)	(0.0353)	(0.0062)	(0.0081)
$PR^{\tau,dw}_{i,t-1}$	0.4023*	0.1491					0.0205	0.0253	0.3914*	0.2662.	-0.0033	0.0308
	(0.1655)	(0.1418)					(0.0341)	(0.0265)	(0.1672)	(0.1581)	(0.0277)	(0.033)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0099	-0.0116	0.0358	0.0197			-0.0153	-0.0029	-0.0094	-0.0134
			(0.0116)	(0.0124)	(0.0263)	(0.0341)			(0.0438)	(0.0436)	(0.0112)	(0.013)
$Spill(A)^{\mu,dw}_{i,t-1}$			-0.0152.	-0.0158	-0.0811*	-0.0994*			-0.0863*	-0.0972*	-0.0118	-0.013
			(0.009)	(0.0119)	(0.0338)	(0.0436)			(0.0403)	(0.0422)	(0.0089)	(0.0129)
$Spill(A)^{\tau,up}_{i,t-1}$	5.165.	5.483*					1.604**	0.4418	5.288.	5.781*	1.571**	0.2136
	(2.795)	(2.658)					(0.5813)	(0.6069)	(2.698)	(2.91)	(0.5445)	(0.6549)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.1467	-0.1639					-0.1211***	-0.0934***	-0.2471.	-0.204	-0.1065***	-0.0985***
	(0.1396)	(0.1185)					(0.0295)	(0.0272)	(0.1438)	(0.1244)	(0.0286)	(0.0278)
AR(1)		0	0	0	0	0	0.0015	0		0	2e-04	0
AR(2)	0.2985	0.2953	0.0014	0.003	0.1809	0.1426	0.1807	0.0227	0.3221	0.2123	0.12	0.011
Sargan	0	0	0.0013	0.007	0	0	8e-04	1e-04	0	0	1e-04	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.8839	0.8934	0.9966	0.9961	0.9347	0.9144	0.9951	0.9958	0.8823	0.885	0.9957	0.9949

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of Suppliers-dominated industries (see (Bogliacino and Pianta, 2016)).

SI.4.5.3. Production-intensive sectors

Table SI.17: Demand-pull and technology-push effects in Production-intensive sectors.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5588***	0.5395***	-0.0447.	-0.034	0.8319***	0.9136***			0.7162***	0.713***	-0.033	-0.0529.
	(0.0402)	(0.0583)	(0.0245)	(0.0295)	(0.0773)	(0.0928)			(0.1022)	(0.095)	(0.0327)	(0.029)
$A^{\tau}_{i,t-1}$	0.4852.	0.1719	1.091***	1.105***			1.151***	1.154***	0.4755	0.1159	1.167***	1.165***
	(0.2807)	(0.2333)	(0.027)	(0.0414)			(0.1501)	(0.0883)	(0.3413)	(0.2732)	(0.1054)	(0.0905)
$PR^{\mu,up}_{i,t-1}$			0.0815.	0.0591	-0.4847**	-0.2179			-0.0561.	-0.0466	0.008	0.0064
			(0.048)	(0.054)	(0.1718)	(0.1765)			(0.0321)	(0.0346)	(0.0077)	(0.0062)
$PR^{\mu,dw}_{i,t-1}$			0.1012*	0.078.	-0.2203	-0.1363			-0.0467	-0.008	0.0112.	0.0119*
			(0.0397)	(0.0421)	(0.2447)	(0.2417)			(0.0393)	(0.034)	(0.0063)	(0.005)
$PR^{\tau,dw}_{i,t-1}$	-1.025	0.3851					0.0969	-0.0581	-0.0146	0.1327	-0.002	-0.0118
	(0.9945)	(0.7106)					(0.5115)	(0.1969)	(0.1453)	(0.0955)	(0.0479)	(0.0308)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0503*	-0.0216	0.1923*	0.2629*			0.0906.	0.0757	-0.0235*	-0.0164
			(0.0215)	(0.0234)	(0.0912)	(0.1053)			(0.0513)	(0.0564)	(0.01)	(0.0102)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0346	0.0403	-0.3194**	-0.3023**			-0.1326**	-0.0913**	5e-04	0.0105
			(0.0237)	(0.0279)	(0.1073)	(0.1125)			(0.0419)	(0.0346)	(0.0071)	(0.0079)
$Spill(A)^{\tau,up}_{i,t-1}$	3.149.	5.418*					2.058*	1.115	8.703***	6.739***	1.544**	0.9693.
	(1.812)	(2.144)					(0.9929)	(0.8112)	(2.187)	(2.022)	(0.5982)	(0.5046)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.183.	-0.2227.					-0.1257**	-0.0909*	-0.2126*	-0.1512	-0.0673**	-0.0544*
	(0.0987)	(0.1289)					(0.0442)	(0.0408)	(0.0981)	(0.0937)	(0.0237)	(0.0233)
AR(1)	0	0	0.0378	0.0344	0	0	0.0416	0.0395		0	7e-04	0.0363
AR(2)	0.9765	0.7431	0.5772	0.6142	0.6127	0.3061	0.1149	0.3658	0.9893	0.9516	0.0072	0.3586
Sargan	0	0	1e-04	0.0052	0	0	0	0	0	0	0	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.922	0.9124	0.9952	0.9946	0.9216	0.9078	0.9946	0.9952	0.8967	0.9004	0.9948	0.995

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of Production-intensive industries (see (Bogliacino and Pianta, 2016)).

SI.4.6. Patent centrality

SI.4.6.1. Sectors with a high centrality in the innovation layer

Table SI.18: Demand-pull and technology-push effects in industries with high patent centrality

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.6268***	0.6175***	-0.0194	-0.0039	0.7156***	0.7603***			0.6905***	0.7776***	0.0103	-0.0024
	(0.0406)	(0.0402)	(0.0176)	(0.017)	(0.0751)	(0.0877)			(0.096)	(0.0778)	(0.019)	(0.0156)
$A^{\tau}_{i,t-1}$	0.3189.	-0.1059	1.134***	1.112***			1.288***	1.283***	0.0176	-0.3977	1.307***	1.299***
	(0.1758)	(0.2666)	(0.0174)	(0.0342)			(0.0686)	(0.0668)	(0.3144)	(0.3537)	(0.0573)	(0.0576)
$PR^{\mu,up}_{i,t-1}$			0.0035	-0.0034	-0.0234	-0.0238			-0.0184	-0.024	-0.0017	-0.0025
			(0.0046)	(0.0061)	(0.0255)	(0.0264)			(0.0327)	(0.0301)	(0.0051)	(0.0041)
$PR^{\mu,dw}_{i,t-1}$			0.0113**	0.0067	0.0133	0.005			0.0159	0.0313	0.0076.	0.0058
			(0.0039)	(0.0055)	(0.031)	(0.0331)			(0.037)	(0.0317)	(0.0044)	(0.0046)
$PR^{\tau,dw}_{i,t-1}$	-0.1004	0.1441					-0.0354	-0.0211	0.0862	0.2605*	-0.0478*	-0.0301
	(0.1101)	(0.0994)					(0.0261)	(0.023)	(0.1376)	(0.1179)	(0.0242)	(0.0193)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0123.	-0.0076	0.0519.	0.0781*			0.0112	0.0232	-0.0083	-0.0044
			(0.0064)	(0.0079)	(0.0277)	(0.0347)			(0.0356)	(0.0377)	(0.0057)	(0.0062)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0055	0.0081	-0.0675*	-0.0515			-0.0915**	-0.0721*	0.0105*	0.012*
			(0.005)	(0.0057)	(0.0288)	(0.032)			(0.0286)	(0.0307)	(0.0048)	(0.005)
$Spill(A)^{\tau,up}_{i,t-1}$	2.676	4.904*					2.495***	1.82***	8.551***	7.328**	2.143***	1.562***
	(1.682)	(2.118)					(0.4845)	(0.4121)	(2.248)	(2.453)	(0.4314)	(0.3562)
$Spill(A)^{\tau,dw}_{i,t-1}$	0.134	-0.0515					-0.0776*	-0.1248***	0.1833	-0.0208	-0.0876**	-0.1343***
	(0.1849)	(0.1341)					(0.0349)	(0.027)	(0.1949)	(0.1495)	(0.0317)	(0.0271)
AR(1)	0	0	0	0	0	0	0	0		0	0	0
AR(2)	0.7376	0.6504	0.0121	0.0164	0.6387	0.4604	0.0455	0.0676	0.6409	0.5191	0.0782	0.105
Sargan	0	0	0	5e-04	0	0	0	3e-04	0	0	0	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9359	0.9221	0.9984	0.9978	0.9357	0.9172	0.9976	0.9981	0.9144	0.9033	0.9981	0.9983

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of industries industries with above median $PR^{\tau,dw}_{i,t}$.

SI.4.6.2. Sectors with a low centrality in the innovation layer

Table SI.19: Demand-pull and technology-push effects in Non-Patent-central sectors.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5915***	0.5691***	0.0194	0.0051	0.8507***	0.8656***			0.774***	0.8428***	0.0191	0.0084
	(0.0488)	(0.0475)	(0.0335)	(0.0339)	(0.0836)	(0.0993)			(0.0855)	(0.0973)	(0.0351)	(0.0362)
$A^{\tau}_{i,t-1}$	0.3181.	0.1905	1.038***	1.006***			1.167***	1.093***	0.2358	0.1918	1.157***	1.102***
	(0.1711)	(0.1636)	(0.0423)	(0.0416)			(0.0738)	(0.0647)	(0.1623)	(0.1838)	(0.0663)	(0.0579)
$PR^{\mu,up}_{i,t-1}$			0.004	0.0031	-0.089***	-0.1136***			-0.0752***	-0.1053***	0.0053	0.0037
			(0.0085)	(0.0094)	(0.0229)	(0.0252)			(0.0225)	(0.0267)	(0.0089)	(0.0097)
$PR^{\mu,dw}_{i,t-1}$			0.0027	0.0019	-0.0425*	-0.0603**			-0.0292	-0.0366.	0.0052	0.0034
			(0.0058)	(0.007)	(0.0201)	(0.0222)			(0.0194)	(0.0217)	(0.0067)	(0.0074)
$PR^{\tau,dw}_{i,t-1}$	-0.3511	-0.6513*					-0.2922.	-0.0739	-0.3931	-0.7966*	-0.2294.	-0.0897
	(0.3047)	(0.2866)					(0.15)	(0.1215)	(0.3048)	(0.3953)	(0.1238)	(0.0864)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0117	-0.0045	0.0981**	0.0766*			0.0799*	0.0404	-0.02.	-0.0076
			(0.0115)	(0.012)	(0.0335)	(0.0343)			(0.0352)	(0.0394)	(0.0121)	(0.0123)
$Spill(A)^{\mu,dw}_{i,t-1}$			-0.003	0.0093	-0.0805	-0.0973*			-0.0862.	-0.118*	-0.0116	0.0046
			(0.0114)	(0.0112)	(0.0503)	(0.0485)			(0.0502)	(0.0485)	(0.011)	(0.0109)
$Spill(A)^{\tau,up}_{i,t-1}$	4.489**	4.793***					2.047***	0.8203	3.781**	4.881**	1.48***	0.7862*
	(1.45)	(1.382)					(0.5552)	(0.6348)	(1.405)	(1.648)	(0.4274)	(0.38)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0134	0.0179					-0.0351	-0.0544*	0.0062	0.0289	-0.0446.	-0.0534*
	(0.0701)	(0.0669)					(0.028)	(0.0231)	(0.0675)	(0.0718)	(0.0257)	(0.0222)
AR(1)	0	0	6e-04	0.0015	0	0	0.0051	0.0035		0	0.0077	0.0027
AR(2)	0.6202	0.5782	0.5707	0.6415	0.6044	0.4946	0.4388	0.5494	0.6391	0.5207	0.4708	0.5109
Sargan	0	0	2e-04	0.0058	0	0	0	0	0	0	0	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9241	0.9258	0.9893	0.9887	0.9255	0.9077	0.9859	0.9862	0.922	0.8927	0.9873	0.9875

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of industries industries with below median $PR^{\tau,dw}_{i,t}$.

SI.4.7. Upstream centrality in the market

SI.4.7.1. Sectors with high upstream centrality in the market

Table SI.20: Demand-pull and technology-push effects in sectors with low upstream centrality in the market.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.541***	0.5399***	0.0053	1e-04	0.5041***	0.6168***			0.4558**	0.6066***	-0.042	-0.0139
	(0.0527)	(0.0522)	(0.0272)	(0.0233)	(0.1438)	(0.1306)			(0.1709)	(0.1278)	(0.0397)	(0.0284)
$A^{\tau}_{i,t-1}$	0.1314	-0.04	1.076***	1.064***			1.02***	1.103***	-0.2172	0.0977	1.07***	1.102***
	(0.177)	(0.1391)	(0.0213)	(0.0303)			(0.1378)	(0.0906)	(0.208)	(0.1461)	(0.1038)	(0.0881)
$PR^{\mu,up}_{i,t-1}$			0.0023	-0.0028	-0.0175	-0.0288			-0.0107	-0.029	0.0015	-0.0054
			(0.0072)	(0.0072)	(0.0202)	(0.0193)			(0.0248)	(0.0185)	(0.0087)	(0.0067)
$PR^{\mu,dw}_{i,t-1}$			0.0098*	0.0035	0.035.	0.0175			0.0365	0.0188	0.0091	0.0028
			(0.004)	(0.0055)	(0.0196)	(0.0209)			(0.023)	(0.0171)	(0.0057)	(0.0061)
$PR^{\tau,dw}_{i,t-1}$	-0.0281	0.0959					0.0938	0.0129	0.169.	0.024	0.0574	0.0177
	(0.092)	(0.0664)					(0.0727)	(0.0392)	(0.0969)	(0.0767)	(0.0497)	(0.0362)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0083	0.0034	0.0118	0.009			0.0131	0.0047	-0.0128	0
			(0.0142)	(0.0133)	(0.0297)	(0.0353)			(0.034)	(0.0347)	(0.0135)	(0.014)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0095	0.0185*	-0.0431	-0.0564.			-0.0303	-0.0525.	0.0132	0.0211*
			(0.0082)	(0.0083)	(0.0281)	(0.032)			(0.0284)	(0.0301)	(0.0084)	(0.0085)
$Spill(A)^{\tau,up}_{i,t-1}$	-1.394	0.8729					1.201	0.7414	-1.681	0.6963	0.7794	0.4497
	(1.345)	(1.449)					(0.8165)	(0.6609)	(1.335)	(1.157)	(0.6945)	(0.6744)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0638	-0.0453					-0.0679*	-0.0529*	-0.0568	-0.1018*	-0.0689**	-0.0574**
	(0.0468)	(0.0502)					(0.0304)	(0.0224)	(0.0533)	(0.0449)	(0.0249)	(0.0219)
AR(1)		0	0.0173	0.0212	0	0		0.0105	0			0.0056
AR(2)	0.2962	0.1914	0.4727	0.4563	0.3395	0.2865			0.4521	0.3225		
Sargan	1e-04	0	0.1012	0.3343	0	0	0.0013	7e-04	0	0	3e-04	4e-04
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9677	0.9568	0.9955	0.9947	0.9692	0.9641	0.9923	0.9944	0.9632	0.9643	0.9941	0.9947

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of industries industries with above median $PR^{\mu,up}_{i,t}$.

SI.4.7.2. Sectors with low upstream centrality in the market

Table SI.21: Demand-pull and technology-push effects in industries with low upstream centrality in the market.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.5954***	0.6013***	0.0168	0.0054	0.7694***	0.7308***			0.687***	0.7137***	0.0158	-0.0026
	(0.0592)	(0.0594)	(0.0206)	(0.0183)	(0.0481)	(0.0601)			(0.0647)	(0.0798)	(0.0226)	(0.0215)
$A^{\tau}_{i,t-1}$	-0.3968	-0.3873.	1.048***	1.041***			0.9603***	1.024***	-0.1949	-0.1691	1.026***	1.033***
	(0.2654)	(0.2182)	(0.0185)	(0.0207)			(0.1021)	(0.0822)	(0.2142)	(0.2291)	(0.0873)	(0.078)
$PR^{\mu,up}_{i,t-1}$			-0.001	8e-04	-0.0394.	-0.0495*			0.0194	-0.0018	0.0096	0.0104
			(0.0075)	(0.0095)	(0.021)	(0.0236)			(0.0316)	(0.0412)	(0.0084)	(0.0101)
$PR^{\mu,dw}_{i,t-1}$			0.0011	0.0026	0.027	-0.0048			0.0771*	0.0413	0.0113.	0.0111
			(0.0047)	(0.0064)	(0.0216)	(0.0227)			(0.0304)	(0.0322)	(0.0068)	(0.0076)
$PR^{\tau,dw}_{i,t-1}$	0.457*	0.3829*					0.129*	0.083.	0.3064*	0.2912.	0.0794.	0.0716.
	(0.1874)	(0.1499)					(0.0594)	(0.0463)	(0.151)	(0.1515)	(0.0467)	(0.0404)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0046	-0.006	0.03	0.0415			0.02	0.0287	-0.0079	-0.0058
			(0.0089)	(0.0098)	(0.0293)	(0.0306)			(0.0341)	(0.0394)	(0.0094)	(0.0103)
$Spill(A)^{\mu,dw}_{i,t-1}$			-0.0034	0.0011	-0.111***	-0.1111**			-0.1291***	-0.1362***	-0.0123	-7e-04
			(0.008)	(0.0078)	(0.0305)	(0.0353)			(0.0335)	(0.0371)	(0.0081)	(0.0078)
$Spill(A)^{\tau,up}_{i,t-1}$	6.88***	7.756**					2.485***	1.769*	6.917***	9.159**	1.994***	1.624*
	(2.08)	(2.613)					(0.6966)	(0.7385)	(1.911)	(3.007)	(0.5419)	(0.6353)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.0305	-0.0296					-0.0513	-0.0591*	-0.0259	-0.0964	-0.0543.	-0.0542*
	(0.1365)	(0.0991)					(0.0395)	(0.0282)	(0.1091)	(0.1012)	(0.0315)	(0.0269)
AR(1)	0	0	0	0	0	0	0	0	0	0	0	0
AR(2)	0.5746	0.5231	0.0435	0.0156	0.5097	0.468	0.4398	0.1059	0.608	0.5916	0.3685	0.1296
Sargan	0	0	4e-04	2e-04	0	0	0	0	0	0	0	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.8405	0.8468	0.9959	0.9952	0.9033	0.9018	0.9906	0.9927	0.8596	0.8411	0.9933	0.9934

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of industries industries with below median $PR^{\mu,up}_{i,t}$.

SI.4.8. Downstream centrality in the market

SI.4.8.1. Sectors with a high downstream centrality in the market

Table SI.22: Demand-pull and technology-push effects in industries with high downstream centrality in the market

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.6307***	0.6515***	0.0269	0.0041	0.8518***	0.7987***			0.7486***	0.8338***	-0.0047	0.0013
	(0.0539)	(0.0451)	(0.0193)	(0.0179)	(0.0688)	(0.0845)			(0.1088)	(0.079)	(0.0297)	(0.0158)
$A^{\tau}_{i,t-1}$	0.2133	0.2429	1.049***	1.036***			0.9432***	1.131***	0.1785	0.103	1.056***	1.111***
	(0.244)	(0.196)	(0.0154)	(0.0241)			(0.1314)	(0.0646)	(0.2848)	(0.2163)	(0.0831)	(0.0587)
$PR^{\mu,up}_{i,t-1}$			-0.0033	-0.0011	-0.0669**	-0.0535.			-0.0323	-0.0469	0.0044	-6e-04
			(0.007)	(0.0082)	(0.0239)	(0.0274)			(0.0344)	(0.0307)	(0.0097)	(0.0076)
$PR^{\mu,dw}_{i,t-1}$			0.0082.	0.0074	-0.0129	-0.0213			0.0018	-0.0052	0.0113.	0.0112*
			(0.0043)	(0.0051)	(0.0199)	(0.0232)			(0.0231)	(0.0206)	(0.006)	(0.0056)
$PR^{\tau,dw}_{i,t-1}$	0.1086	0.0517					0.1528*	0.0011	0.1513	0.0864	0.0713	0.0024
	(0.153)	(0.085)					(0.0734)	(0.024)	(0.1743)	(0.0773)	(0.0447)	(0.0212)
$Spill(A)^{\mu,up}_{i,t-1}$			-0.0167.	-0.0118	0.0643*	0.0735*			0.0733*	0.0552.	-0.0172.	-0.0144
			(0.0086)	(0.0094)	(0.0279)	(0.0315)			(0.033)	(0.0319)	(0.0102)	(0.0088)
$Spill(A)^{\mu,dw}_{i,t-1}$			-0.0031	7e-04	-0.0809.	-0.0606			-0.084.	-0.086*	-0.0062	0.0035
			(0.0087)	(0.0095)	(0.0426)	(0.0427)			(0.051)	(0.043)	(0.0106)	(0.0083)
$Spill(A)^{\tau,up}_{i,t-1}$	4.756*	4.962**					3.159**	0.5732.	7.422***	6.19***	1.995***	0.6129*
	(1.932)	(1.767)					(0.9771)	(0.3377)	(2.047)	(1.766)	(0.5722)	(0.3068)
$Spill(A)^{\tau,dw}_{i,t-1}$	-0.1115	-0.1055					-0.0438	-0.0554*	-0.1055	-0.0564	-0.0528	-0.0458.
	(0.0823)	(0.0784)					(0.0478)	(0.0251)	(0.1003)	(0.0856)	(0.0335)	(0.0239)
AR(1)		0	0	0	0	0	0.0047	0		0	0	0
AR(2)	0.9448	0.8598	0.7496	0.8759	0.9467	0.3926	0.7496	0.9705	0.7994	0.8165	0.8528	0.9764
Sargan	0	0	1e-04	0.1108	0	0	6e-04	0	0	0	1e-04	0
Controls		Y		Y		Y		Y		Y		Y
R^2	0.903	0.9045	0.9959	0.9949	0.9112	0.8962	0.9848	0.9955	0.8816	0.8953	0.9921	0.9955

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of industries industries with above median $PR^{\mu,dw}_{i,t}$.

SI.4.8.2. Sectors with a low downstream centrality in the market

Table SI.23: Demand-pull and technology-push effects in sectors with a low downstream centrality in the market.

	Type 1				Type 2				Both			
	$\tau \to \mu$		$\mu \to \tau$		Market		Innovation					
	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\mu}_{i,t}$	$A^{\tau}_{i,t}$	$A^{\tau}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$A^{\mu}_{i,t-1}$	0.594***	0.5005***	-0.0221	-0.0253	0.472***	0.4261***			0.4649***	0.4814***	-0.0388	-0.0224
	(0.0555)	(0.0527)	(0.0355)	(0.0362)	(0.0735)	(0.0899)			(0.0829)	(0.0896)	(0.0376)	(0.0378)
$A^{\tau}_{i,t-1}$	-0.1408	-0.3558.	1.066***	1.052***			1.094***	1.058***	0.1376	-0.4097	1.098***	1.061***
	(0.2237)	(0.2154)	(0.0315)	(0.035)			(0.1424)	(0.0733)	(0.3105)	(0.2783)	(0.1309)	(0.0793)
$PR^{\mu,up}_{i,t-1}$			0.0144.	0.0122.	-0.0013	-0.0163			0.0078	-0.0216	0.0074	0.0071
			(0.0084)	(0.0069)	(0.0263)	(0.0238)			(0.0306)	(0.0243)	(0.008)	(0.0071)
$PR^{\mu,dw}_{i,t-1}$			-0.017*	-0.017*	0.0484	0.033			0.0519	0.0201	-0.0193**	-0.0226**
			(0.0081)	(0.0083)	(0.0306)	(0.0302)			(0.0357)	(0.0322)	(0.0067)	(0.0081)
$PR^{\tau,dw}_{i,t-1}$	0.0222	0.1383					0.0141	0.0304	-0.2027	0.0798	0.0038	0.0297
	(0.1298)	(0.1215)					(0.0704)	(0.0451)	(0.1915)	(0.1464)	(0.067)	(0.0405)
$Spill(A)^{\mu,up}_{i,t-1}$			0.0022	0.0125	0.0865**	-0.0156			0.0424	-0.0166	0.0011	0.0177
			(0.0117)	(0.0123)	(0.0324)	(0.0414)			(0.0404)	(0.0462)	(0.011)	(0.0136)
$Spill(A)^{\mu,dw}_{i,t-1}$			0.0011	0.0083	0.0317	-0.0342			0.0048	-0.0439	-0.0016	0.0077
			(0.0086)	(0.0089)	(0.0281)	(0.0313)			(0.0314)	(0.0323)	(0.0087)	(0.0085)
$Spill(A)^{\tau,up}_{i,t-1}$	4.632**	1.952					1.839***	0.7189.	5.329*	1.241	1.564**	0.5707
	(1.697)	(1.528)					(0.4848)	(0.4341)	(2.219)	(1.608)	(0.5233)	(0.4725)
$Spill(A)^{\tau,dw}_{i,t-1}$	0.07	0.024					-0.061*	-0.0465*	0.0797	0.061	-0.0563*	-0.0491*
	(0.0516)	(0.0532)					(0.0279)	(0.0203)	(0.0604)	(0.0629)	(0.0275)	(0.0231)
AR(1)	0	0	0.0365	0.0269	0	0		0.0163		0		0.0188
AR(2)	0.873	0.9963	0.8164	0.7997	0.9125	0.8953		0.5992	0.6816	0.9007		0.7343
Sargan	0	0	0	0	0	0	0	0	0	0	0	1e-04
Controls		Y		Y		Y		Y		Y		Y
R^2	0.9516	0.9495	0.9955	0.9955	0.9597	0.9405	0.9952	0.995	0.9417	0.9396	0.9955	0.995

Notes: The table shows the regression results of output $A^{\mu}_{i,t}$ and patents $A^{\tau}_{i,t}$ on demand-pull and technology-push effects. The estimation is based on a two-ways Blundell-Bond (BB) system GMM model using a one-step estimation procedure. Spillovers are calculated on the basis of first-order links. Variables measured in monetary terms are deflated using the industry level price deflators for the value of shipment obtained from the NBER-productivity database (Becker et al., 2013). Instruments are collapsed to avoid instrument proliferation. To cope with skewness and to obtain tractable coefficients, most variables are pre-processed (taking logs, removing outliers, scaling). Data in logs are $A^{\alpha}_{i,t}$, $PR^{\alpha,d}_{i,t}$, $Spill(A)^{\alpha,d}_{i,t}$, $L_{i,t}$, $(K/L)_{i,t}$, $(I/L)_{i,t}$, $W_{i,t}$, $(K/L)_{ij,t-1}$, $(E/L)_{ij,t-1}$, $(M/L)_{ij,t-1}$, $W^{P}_{ij,t-1}$ with $\alpha = \mu, \tau$ and $d = up, dw$. A detailed description of the transformations and descriptive statistics of the regression data before and after the transformations are provided in A.1. The rows AR(1), AR(2), and Sargan show the test statistics of the specification tests, i.e. testing for first- and second-order autocorrelation and the results of a Sargan test for validity of instruments (see Roodman, 2009). The analysis covers the subset of industries industries with below median $PR^{\mu,dw}_{i,t}$.