Essays on Digitalization and Firm Performance

Daniel Bonvin

Under the supervision of María Dolores Añón Higón

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Resumen

Esta tesis doctoral analiza cómo el uso de las tecnologías digitales (TD) afecta las decisiones de las empresas en el comercio internacional y el empleo. La rápida expansión de estas tecnologías ofrece oportunidades para reducir costes asociados a la distancia física, lo que permite a las empresas llegar a más clientes y ampliar sus mercados. Sin embargo, el hecho de que las TD también puedan ser sustitutas de la mano de obra, remplazando a los humanos en sus trabajos y aumentando potencialmente el desempleo, suscita preocupación. Así pues, estos dos temas serán abordados en la tesis. Primer, los Capítulos 1[1] y 2 se centrarán en el impacto de la digitalización en el comercio internacional. Más concretamente, en el Capítulo 1 exploramos cómo el uso de las tecnologías de la información y la comunicación (TIC) facilita las exportaciones de las empresas. El Capítulo 2 pretende aportar pruebas sobre el impacto de las TD, más allá de las TIC, en las actividades de exportación e importación de las pequeñas y medianas empresas (PYMEs). En esta perspectiva, construimos un índice multidimensional de digitalización para captar la transformación digital de una forma más exhaustiva. En segundo lugar, esta tesis explora cómo las TD afectan a la demanda laboral de las empresas. El Capítulo 3 pretende aportar evidencia sobre esta cuestión, estudiando cómo el grado de digitalización, medido por el índice construido en el Capítulo 2, afecta a la demanda de empleo de las empresas.

El primer objetivo de esta tesis es demostrar que las TD pueden ayudar las empresas manufactureras españolas a aumentar su competitividad en el mercado exterior. De hecho, las tecnologías de la información y la automatización están reconfigurando nuestra economía y, en particular, la organización de las empresas y su proceso de producción. Además, la difusión de las TD ha supuesto un avance hacia la globalización y el comercio internacional. La digitalización ha permitido la reducción de las barreras comerciales al disminuir los costes del comercio a través de diferentes canales (Venables, 2001). En primer lugar, las TD mejoran la transparencia del mercado, que es un requisito previo esencial para el intercambio, reduciendo así los costes de búsqueda, emparejamiento y

[1] Este capítulo ha sido publicado como Añón Higón, D., and Bonvin, D. (2022). Information and communication technologies and firms' export performance. *Industrial and Corporate Change,* 31(4): 955-979.

comunicación entre consumidores y proveedores a nivel internacional (Hagsten, 2015). En segundo lugar, las TD pueden proporcionar a las empresas canales adicionales para la comercialización y las ventas, permitiéndoles llegar a un mayor número de clientes conectados digitalmente. Además, las TD permiten a las empresas externalizar sus insumos y organizar la producción de manera más eficiente, lo que se traduce en un aumento de la productividad (Fernandes *et al*., 2019). Las TD también pueden ayudar a las empresas a innovar y mejorar así su productividad (Brynjolfsson y Saunders, 2009). Este aumento de la productividad puede inducir a las empresas a exportar o a aumentar sus ventas en el extranjero (Bernard y Jensen, 1999). Estos beneficios potenciales de la transformación digital pueden ser aún mayores para las PYMEs, ya que puede contribuir a reducir los costes de internacionalización relacionados con su tamaño y la dificultad que estas tienen para comprometer recursos financieros y humanos.

Sin embargo, a pesar de tener un efecto positivo en el comercio, como vamos a ver en los Capítulos 1 y 2, el impacto de la digitalización en el empleo es más incierto. El segundo objetico de esta tesis es determinar si la digitalización influye negativamente en la demanda de empleo, y a quién beneficia, o, por el contrario, quién se ve más afectado por la transformación digital. Sin duda, la introducción de nuevas tecnologías es potencialmente perturbadora para determinadas ocupaciones, ya que es probable que algunas sean sustituidas por máquinas. Sin embargo, esta sustitución potencial crea nuevos trabajos en los que se necesitan personas. Esto es lo que Schumpeter (2013) describe como destrucción creativa. No obstante, nuevas tecnologías, como la robotización, tienen el potencial de ser más perturbadoras, ya que pueden realizar tareas que requieren habilidades humanas. La digitalización, y más concretamente las tecnologías de automatización, pueden sustituir al ser humano en sus tareas. A ello nos referiremos como efecto potencial de sustitución. A su vez, la digitalización permite a las empresas llegar a más compradores y ampliar su mercado, como se ha demostrado anteriormente en los Capítulos 1 y 2, y, por tanto, ampliar su demanda. A ello nos referiremos como el efecto escala de la demanda. Por último, a través del efecto productividad, las TD permiten a las empresas organizar su producción de forma más eficiente, aumentar su productividad y, por tanto, incrementar la demanda de trabajo. Para ver si el impacto de la digitalización en el empleo es positivo o negativo, tenemos que saber qué efecto domina. Este es el objetivo del último capítulo. Para alcanzar dichos objetivos, utilizaremos la base de datos de la *Encuesta sobre Estrategias Empresariales* (ESEE). es una base de datos de panel anual realizada desde 1990 y que es representativa de la población de empresas manufactureras españolas con diez o más empleados. Está patrocinada por el Ministerio de Industria, Turismo y Comercio de España y gestionada por la Fundación SEPI. La ESEE proporciona información sobre las estrategias de las empresas, es decir, las decisiones que éstas toman en relación con sus competidores. El cuestionario incluye información sobre la actividad de la empresa, productos y procesos de fabricación, clientes y proveedores, costes y precios, mercados, datos contables y, para los objetivos de esta investigación, información sobre actividades tecnológicas, comercio exterior y empleo.

En el Capítulo 1, nos centramos en primer lugar en el uso de las TIC y su papel en las actividades exportadoras de las empresas manufactureras españolas. El análisis se realiza a partir de datos a nivel de empresa extraídos de la ESEE, que proporciona información sobre las empresas manufactureras españolas entre 1990 y 2014. Sin embargo, dado que sólo se dispone de información del uso de aplicaciones TIC desde el año 2000, el periodo de análisis en el Capítulo 1 abarca desde 2000 hasta 2014. En este primer capítulo, nos centramos en el uso de las TIC, y para ello consideramos las respuestas a las siguientes preguntas de la ESEE: si las empresas tienen página web; si venden en línea a otras empresas o a consumidores finales; y si compran bienes o servicios en línea. Se considera que una empresa es usuaria de las TIC si responde afirmativamente a alguna de las preguntas anteriores. Esta información, junto con la información sobre si la empresa es exportadora o no, nos permitirá estudiar la relación entre el uso de las TIC y la probabilidad de exportar. También exploramos el impacto del uso de las TIC en la intensidad de las exportaciones, es decir, la proporción de ventas en el extranjero sobre el total. Además, el impacto de las TIC sobre las exportaciones se divide en dos efectos distintos, un efecto directo y un efecto indirecto. El primero es simplemente el efecto escala de la demanda derivado del uso de las TIC sobre la probabilidad de exportar, mientras que el segundo es el efecto de las TIC sobre las exportaciones a través de las mejoras en la productividad total de los factores (PTF). Al utilizar un proceso de Markov endógeno en la estimación de la PTF, permitimos que las TIC influyan en la productividad. Para la existencia del efecto indirecto, las TIC deben tener un impacto significativo y positivo en la PTF y la misma condición debe cumplirse para el efecto de la PTF en las exportaciones.

En el primer capítulo, el modelo utilizado para estimar los efectos directos e indirectos del uso de las TIC en la propensión a exportar se basa en el modelo de Roberts y Tybout (1997). En consecuencia, las empresas deciden exportar cuando los ingresos actuales y previstos superan los costes actuales, incluidos los costes de entrada irrecuperables que vienen recogidos por la situación de exportación de la empresa en el período anterior. Esto implica el uso de una especificación dinámica para modelizar la participación en las exportaciones. Así, suponemos que la empresa decide exportar si el valor actual esperado de los beneficios de la exportación es positivo. En el modelo, incluimos el uso de las TIC, la PTF, la situación previa de exportación y un vector de variables explicativas que la literatura ha demostrado que explican el estatus exportador. Todas las variables están rezagadas un periodo para evitar problemas de simultaneidad. Además, consideramos el efecto no observado específico de la empresa, los efectos fijos de la industria y los efectos temporales. El efecto de otros determinantes inobservables específicos de la empresa y del periodo se resume en el término de error. Sin embargo, existe una preocupación en la estimación de este modelo debido al sesgo causado por el problema de la condición inicial (Heckman, 1981) y la correlación potencial entre el término de heterogeneidad no observada y las covariables. Para abordar simultáneamente estas cuestiones, seguimos a Wooldridge (2005), que sugiere modelar la heterogeneidad no observada como una función de la condición inicial, i.e., la primera observación de la variable dependiente (la propensión a exportar), y otras covariables. Por lo tanto, el término de heterogeneidad no observada se modela con las medias temporales de las variables de control que estén probablemente correlacionadas con él, i.e., las medias Mundlak-Chamberlain (Chamberlain, 1982; Mundlak, 1978). En este sentido, y para aliviar los problemas de correlación entre las covariables y sus medias temporales, seguimos a Semykina (2018). Ello implica asumir en la especificación de referencia que los efectos individuales no observados solo están correlacionados con las condiciones financieras internas y externas de la empresa y las condiciones de apropiabilidad. En el contexto actual, estas medias temporales pueden interpretarse como medidas de la estabilidad financiera de la empresa, que también pueden considerarse como aproximaciones de las características no observadas específicas de la empresa (por ejemplo, la calidad de la gestión).

Para modelizar el efecto del uso de las TIC en la intensidad de las exportaciones, es necesario considerar la selección no aleatoria que lleva a algunas empresas a exportar, lo que es coherente con la hipótesis de autoselección. Para ello, estimamos un modelo dinámico Tipo II-Tobit con el procedimiento en dos etapas de Heckman, que permite que los dos procesos, la selección en la exportación y la intensidad, estén correlacionados (Heckman, 1979). La identificación del modelo requiere una restricción de exclusión, es decir, debe identificarse al menos un factor que influya en la participación en las exportaciones, pero no en su intensidad. Utilizamos el estado de exportación anterior como restricción de exclusión sobre la base de que es una variable sustitutiva de los costes irrecuperables de entrar en mercados extranjeros y, por lo tanto, solo afecta al margen extensivo (Brancati *et al*., 2018).

Nuestros resultados sugieren que las empresas que utilizan las TIC experimentan un aumento directo de la probabilidad de exportar, pero no de la intensidad exportadora. No obstante, la intensidad exportadora aumenta con las TIC debido a las ganancias de productividad (por el canal indirecto de la PTF). Sin embargo, estos resultados varían según el tamaño de la empresa y el sector. En cuanto al tamaño, observamos que las PYMEs se benefician directamente de las TIC para participar en los mercados extranjeros y, una vez que ya están en estos mercados, se benefician indirectamente, a través de la PTF, al aumentar su cuota de exportación. Las grandes empresas, por el contrario, sólo se benefician a través de las ganancias de PTF en el margen intensivo. Además, el uso de las TIC, y en particular la existencia de una página web, parece influir positivamente en la decisión de exportar o no para las empresas de industrias poco digitalizadas, pero no tiene ningún efecto directo en las empresas de industrias muy digitalizadas. Por el contrario, las TIC en las industrias altamente digitalizadas fomentan la intensidad exportadora tanto directamente como a través del canal de la PTF.

Los resultados del Capítulo 1 revelan que las PYMEs tienen más que ganar con el uso de las TIC. Esto, unido al hecho de que se enfrentan a más barreras para entrar en mercados internacionales, es la razón por la que en el Capítulo 2 nos centramos únicamente en este tipo de empresas. Aquí, en lugar de centrarnos únicamente en las TIC, ampliamos el análisis para considerar otras dimensiones de la transformación digital. Por lo tanto, utilizando también la ESEE, en el Capítulo 2 construimos un índice multidimensional de digitalización siguiendo a Calvino *et al.* (2018) con el objetivo de captar mejor este complejo fenómeno. A diferencia de Calvino *et al.* (2018), el índice de digitalización es a nivel de empresa. Este índice engloba un total de 13 componentes diferentes que representan cuatro dimensiones de la transformación digital. Estas dimensiones son los componentes tecnológicos, el capital humano relacionado con lo digital, el alcance de la automatización y la forma en que la digitalización cambia la forma en que las empresas interactúan con terceros. Así, en el Capítulo 2, se evalúa el impacto directo e indirecto (a través de la PTF) de la digitalización no sólo en la decisión de exportar, sino también de importar. Al utilizar un proceso de Markov endógeno para modelizar la PTF, como en el primer capítulo, permitimos que el índice de digitalización y el estatus exportador o importador de la empresa influyan en la productividad.

Para estimar el efecto de la digitalización en la probabilidad de comerciar internacionalmente, procedemos con la misma metodología que en el Capítulo 1, con la excepción de que tenemos dos modelos, uno para la decisión de exportar y otro para la de importar. Procedemos estimando ambas decisiones de participación en los mercados extranjeros de forma simultánea (Elliott *et al*., 2019; Exposito y Sanchis-Llopis, 2020). Para ello utilizamos el Conditional Mixed Process (CMP) implementado por Roodman (2011).

Los resultados del Capítulo 2 muestran que la digitalización facilita directamente tanto la participación en las exportaciones como en las importaciones. Además, nuestros resultados también aportan pruebas de un efecto indirecto de la digitalización a través de la productividad sobre la decisión de comerciar. El efecto directo parece ser mayor para las exportaciones que para las importaciones, mientras que esta observación se invierte cuando se considera el efecto indirecto. Los resultados de este capítulo también están sujetos a heterogeneidad. Curiosamente, las empresas pertenecientes a industrias poco digitalizadas parecen beneficiarse más de la digitalización que sus homólogas pertenecientes a industrias muy digitalizadas. Las empresas de sectores poco digitalizados, gracias a las TD, son capaces de adquirir una ventaja comparativa en comparación con las empresas que no adoptan las TD. Por último, para distinguir entre dos tipos diferentes de tecnologías, desglosamos el índice de digitalización en dos subíndices, el índice TIC y el índice de automatización. Es probable que las tecnologías TIC fragmenten el proceso de producción reduciendo algunos costes asociados a la distancia física y aumentando así el comercio. Las tecnologías de automatización pueden sustituir a personas en sus puestos de trabajo, relocalizar algunas tareas que antes se externalizaban al extranjero y, por tanto, reducir el comercio. Los resultados que obtenemos en este capítulo tienden a confirmar esta intuición.

En efecto, las TIC tienen un efecto directo sobre la probabilidad de exportar e importar, mientras que la automatización no tiene ningún impacto.

A pesar de los resultados positivos encontrados en los anteriores capítulos, la transformación digital también suscita preocupación por la automatización de los puestos de trabajo y el posible aumento del desempleo. Esto provoca un temor muy tangible entre los empleados cuyos puestos de trabajo se ven amenazados por las TD y constituye, por tanto, una importante cuestión social. Habiendo observado en los capítulos anteriores el aumento de la demanda y de la eficiencia debido a la adopción de la tecnología digital, nuestro objetivo en el Capítulo 3 es responder a la pregunta de si la digitalización reduce efectivamente el empleo en el caso concreto de las empresas manufactureras españolas.

En el Capítulo 3, examinamos el efecto de la digitalización en la demanda laboral de las empresas. Para ello, de nuevo, utilizamos los datos de la ESEE y el índice de digitalización construido en el Capítulo 2. Como se mencionó anteriormente, argumentamos que la digitalización puede afectar al empleo a través de tres canales diferentes: el efecto escala de la demanda, el efecto sustitución potencial y el efecto productividad. En nuestro análisis, sin embargo, debido a la falta de datos sobre los precios de los activos digitales, no podemos disociar el efecto de sustitución potencial del efecto escala de la demanda. Esto implica que sólo podemos identificar una combinación de estos dos efectos, que denominamos efecto directo de la digitalización, y estimar cuál domina observando el signo del coeficiente.

En nuestro modelo, para tener en cuenta la competencia imperfecta y la existencia de empresas que maximizan beneficios, seguimos el marco de Ortiz y Salas Fumás (2020) y, por tanto, consideramos el poder de mercado en la estimación de la demanda de empleo. Partimos de una función de producción Cobb-Douglas en la que la producción depende del capital, el trabajo y los insumos intermedios. Consideramos que la elasticidad de la producción con respecto a cada insumo toma valores entre 0 y 1. Además, se incorpora un parámetro que representa la eficiencia técnica del proceso de producción. De hecho, suponemos que la digitalización permite a las empresas externalizar los insumos de forma más eficiente, así como innovar (Tambe y Hitt, 2014). Por lo tanto, tener en cuenta el papel potencial de la digitalización en la mejora de la PTF implica modelizar la productividad como un proceso de Markov endógeno que permite que el índice de digitalización influya en la productividad, ya que pretendemos evaluar el impacto directo e indirecto (a través de la PTF) de la digitalización en la demanda laboral. A continuación, resolvemos el problema de maximización de beneficios de la empresa y obtenemos la demanda de trabajo. Aquí di esa demanda de trabajo de que depende

Uno de los problemas a la hora de estimar la función de demanda de empleo, es la posible endogeneidad del índice de digitalización, que resolvemos con el método de variables instrumentales (VI). El enfoque de VI para estimar nuestro modelo se basa en un procedimiento de estimación por mínimos cuadrados en dos etapas (2SLS). Primero instrumentamos el índice de digitalización con su segundo retardo, que suponemos está correlacionado con el índice de digitalización, pero no con el término de error. Según la literatura, es habitual utilizar variables retardadas como instrumentos (por ejemplo, Cameron *et al*., 2005). En la primera etapa, realizamos una regresión del índice de digitalización sobre su segundo retardo y el resto de las variables de control utilizadas en el modelo de la segunda etapa utilizando una especificación de efectos fijos (EF). En la segunda etapa, los valores estimados del modelo de la primera etapa se utilizan en lugar de los valores originales del índice de digitalización para estimar un modelo de efectos fijos (EF) y evitar así cualquier problema de simultaneidad.

Para examinar el impacto de la digitalización en la composición de la mano de obra, utilizamos la proporción de categorías de trabajadores como variable dependiente, con el mismo modelo presentado anteriormente. La variable dependiente representa los siguientes porcentajes respecto al empleo total: i) empleo no cualificado, ii) empleo cualificado, iii) empleo en la industria manufacturera, iv) trabajadores fijos y v) trabajadores temporales. El hecho de que la variable dependiente sea una proporción implica que los valores de la variable dependiente están acotados entre 0 y 1. Por lo tanto, un modelo de regresión lineal como mínimos cuadrados ordinarios no es apropiado (Kölling, 2020). En su lugar, utilizamos un modelo fraccional para datos de panel (Papke y Wooldridge, 2008; Wooldridge, 2010). Además, para controlar la endogeneidad potencial del índice de digitalización, seguimos a Kölling (2020) y aplicamos un enfoque de función de control (FC) y lo tratamos como un problema de variables omitidas (Wooldridge, 2015). La FC consta de dos pasos. En el primer paso, realizamos una regresión del índice de digitalización sobre el segundo retardo del índice de digitalización y las covariables del modelo empírico en un modelo de efectos fijos. En el segundo paso, el residuo de la regresión del primer paso se utiliza como una covariable adicional en función de trabajo para tener en cuenta los factores que pueden causar la correlación entre el índice de digitalización y el término de error. Nuestra estrategia de identificación reside en el hecho de que el grado de digitalización de hace dos periodos no influye en las decisiones actuales de las empresas sobre el empleo y sus componentes, excepto a través de la digitalización.

Las conclusiones del Capítulo 3 muestran un efecto directo positivo, así como un efecto de productividad, de la digitalización sobre la demanda laboral de las empresas. Además, este efecto persiste cuando se considera la demanda, en términos absolutos, de trabajadores altamente cualificados, poco cualificados o en actividades manufactureras, lo que implica que la creación de tareas supera a su destrucción. Sin embargo, cuando analizamos los porcentajes en lugar de los valores absolutos, los resultados muestran diferencias importantes. Así, la proporción de trabajadores poco cualificados y en actividades de producción se ve afectada negativamente por la digitalización, al contrario que la proporción de trabajadores altamente cualificados, lo que aporta pruebas a favor del sesgo del cambio tecnológico hacia la mano de obra altamente cualificada. De hecho, las TD crean nuevas tareas en todos los niveles de cualificación, pero los empleos cualificados representan una mayor proporción del total de nuevos empleos creados que los no cualificados. Además, esto podría suscitar preocupaciones sobre las posibles desigualdades causadas por las disparidades salariales como consecuencia de este sesgo. Por último, al igual que en el Capítulo 2, desglosamos el índice de digitalización en dos subíndices, el índice de automatización y el índice TIC, para captar el posible impacto diferenciado de estas tecnologías. Mientras que las TIC afectan a la demanda laboral, la automatización no tiene un impacto significativo. Esto es coherente con el hecho de que es más probable que las TIC complementen a los trabajadores y que las tecnologías de automatización, como los robots, tiendan a sustituirlos.

Las contribuciones a la literatura sobre comercio internacional y organización industrial a lo largo de esta tesis son múltiples. En primer lugar, en todos los capítulos estimamos no sólo el impacto directo de la digitalización en los resultados de las empresas (es decir, el comercio o el empleo), sino también el efecto indirecto a través de la productividad. Desde esta perspectiva, permitimos que la digitalización (o las TIC) afecten a la productividad futura mediante un proceso de Markov endógeno. En segundo lugar, en los Capítulos 1 y 2, modelizamos la participación en el mercado exterior utilizando un modelo dinámico para tener en cuenta las experiencias comerciales previas. En tercer lugar, en el Capítulo 2, estimamos las decisiones de exportar e importar simultáneamente para examinar la interdependencia de estas dos actividades. En cuarto lugar, en este capítulo introducimos el índice de digitalización, que es una de las principales contribuciones de esta tesis, ya que es, hasta donde sabemos, el primer estudio que construye un índice representativo de la transformación digital de las empresas manufactureras españolas. Este índice de digitalización, que también utilizamos en el Capítulo 3, engloba varias dimensiones de la transformación digital y nos permite captar este fenómeno de una forma más completa que utilizando indicadores aislados del fenómeno. Por último, en el Capítulo 3, seguimos el marco de Ortiz y Salas Fumás (2020) y consideramos empresas maximizadoras de beneficios. Esto implica estimar una función de demanda de trabajo que también depende de los determinantes de la demanda de productos, y, por tanto, del poder de mercado, los cuales no son relevantes bajo el enfoque estándar de minimización de costes.

Los resultados obtenidos a lo largo de esta tesis pueden tener importantes implicaciones para la gestión empresarial. Las empresas, en particular las PYMEs, pueden aumentar sus probabilidades de exportar e importar adoptando las tecnologías de la información y la comunicación, en particular las aplicaciones TIC básicas como una página web, tal y como se muestra en el Capítulo 1 y Capítulo 2. La digitalización ayuda a las PYMEs a superar la desventaja de recursos que tienen en comparación con sus homólogas de mayor tamaño. En efecto, las tecnologías de la información permiten a las empresas reducir costes y dar a conocer sus productos en todo el mundo para llegar a más clientes. Además, como se ha visto en el Capítulo 3, el proceso de digitalización puede realizarse sin la preocupación de tener que reducir el empleo total a causa de la automatización de algunas tareas por las nuevas tecnologías. La destrucción de tareas sustituidas por máquinas se compensa con la creación de nuevas tareas que requieren el mismo tipo de competencias. Sin embargo, es importante precisar que, según nuestros resultados, los empleos cualificados se verán abocados a representar una mayor proporción del empleo total en detrimento de los empleos no cualificados.

En cuanto a las recomendaciones de política pública, los resultados aquí presentados muestran claramente que la digitalización mejora la competitividad española en los mercados exteriores sin obstaculizar el empleo local. Por estas razones, se debería incentivar a las empresas para que avancen hacia un mayor nivel de digitalización. Subvenciones o desgravaciones fiscales animarían a las empresas a adoptar las TD y promoverían la transformación digital de la economía. Este apoyo gubernamental puede ser especialmente importante para las PYMEs, que están sometidas a una mayor presión financiera que las empresas más grandes y van rezagadas en cuanto a la integración de las nuevas tecnologías. En este sentido, se ha desarrollado el plan de digitalización de las PYMEs 2021-2025 para impulsar la digitalización básica y más innovadora de las PYMEs españolas. Estos incentivos podrían ayudar a las PYMEs a entrar en mercados extranjeros y ganar competitividad. Además, la digitalización tiene un efecto positivo general en el empleo de las empresas. Sin embargo, como se informó en el Capítulo 3, las TD están sesgadas hacia la mano de obra altamente cualificada, lo que podría aumentar desproporcionadamente su demanda, haciéndola más valiosa. En este sentido, según Juhn *et al*. (1993), cuando aumenta la demanda de cualificaciones, aumenta también el rendimiento de las mismas, y se profundizan las desigualdades salariales entre los trabajadores poco cualificados y los muy cualificados. Por lo tanto, deben ofrecerse cursos de formación en digitalización a la población activa para preparar la transición hacia estas nuevas tareas. En esta línea, el programa *Next Generation* de la Unión Europea ha puesto en marcha iniciativas para financiar cursos de formación en línea para mejorar las competencias digitales con el fin de ayudar a las PYMEs a aumentar su presencia en línea y hacer más accesible la educación en línea. A nivel nacional, la estrategia España Digital 2026 pretende invertir en infraestructuras, como la conectividad de banda ancha, la inteligencia artificial o el 5G, promover la digitalización de la economía, con especial atención a las PYMEs, y mejorar las competencias digitales de la población española.

En general, la clave para apoyar la transformación digital de la economía es adoptar un enfoque holístico que tenga en cuenta las necesidades tanto de las empresas como de los trabajadores. Prestando apoyo a las empresas para que adopten tecnologías digitales y a los trabajadores para que adquieran las competencias que necesitan para tener éxito en la economía digital, los responsables políticos pueden contribuir a garantizar que los beneficios de la digitalización sean ampliamente compartidos y que la economía pueda seguir prosperando en la era digital.

No obstante, esta tesis no está exenta de limitaciones que podrían aportar interesantes sugerencias para futuras investigaciones. Por ejemplo, los datos sobre el destino de las exportaciones y la procedencia de las importaciones nos permitirían verificar la hipótesis de la muerte de la distancia, en la que la transformación digital contribuye a eliminar las barreras geográficas tradicionales y hace más accesible exportar a países más lejanos e importar desde ellos. El índice de digitalización construido en el capítulo 2 recoge varias dimensiones de la transformación digital, así como numerosas TD, y es representativo del progreso tecnológico durante el periodo de análisis (2000-2014). Sin embargo, la información sobre las tecnologías de la Industria 4.0, como la IA, el aprendizaje automático, la impresión 3D, etc. nos permitiría captar la transformación digital de forma más exhaustiva y ver si su adopción ha permitido acelerar o ralentizar el proceso de globalización. Específicamente en el Capítulo 3, carecemos de datos sobre los precios de los activos, lo que nos permitiría desligar el efecto demanda-escala del potencial efecto sustitución de la TD sobre el empleo. Además, los datos no proporcionan información sobre diferentes ocupaciones o niveles de rutinización de las tareas laborales, que es un elemento importante para determinar qué grupos de trabajadores se ven más amenazados por la digitalización. Estos datos podrían utilizarse para ver si los trabajos rutinarios corren más riesgo de automatización que los no rutinarios. Además, los datos sobre el nivel de rutinización de las tareas podrían emparejarse con datos sobre los niveles de cualificación para detectar si los trabajos rutinarios tienen más probabilidades de ser automatizados, aunque requieran una elevada cualificación.

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Introduction

This doctoral thesis presents research on how the use of digital technologies (DTs) affects firms' decision-making in international trade and employment. DTs are spreading rapidly and offer opportunities to reduce some costs associated with physical distance, allowing firms to reach additional customers and expand their markets. However, concerns arise from the fact that these technologies can also be labor substitutes, thus replacing humans in their tasks and potentially increasing unemployment. In Spain, the focus of our analysis, DTs tend to be more widespread than the European Union (EU) average. In fact, according to the 2022 edition of the Digital Economy and Society Index (DESI), which tracks the progress made by EU Member States in digital competitiveness, Spain ranks 7th out of the 27 EU Member States. This index is composed by several dimensions, being the integration of DTs by businesses the weakest dimension, despite the important progress made. This is due to the fact that Spanish enterprises in general, and SMEs in particular, are lagging behind in the integration of new technologies such as cloud or big data[2]. Therefore, it is particularly interesting to analyze whether the (uneven) digital transformation process has had an impact on Spanish firms in general, and specifically on SMEs. To this end, in this thesis we will explore how the process of digitalization endured by Spanish firms in the last two decades has affected both their trade activities and their demand for labor.

To explore the impact of DTs on trade and employment, this thesis adopts a three-essay format and draws on concepts and theories from various strands of the literature on the intersection of international trade, labor, firm dynamics, and industrial organization. First, Chapters 1[3] and 2 both focus on how digitalization impacts international trade. More specifically, in Chapter 1, we explore how the use of information and communication technologies (ICTs) facilitates firms' exports. Chapter 2 aims to provide evidence on the impact of DTs, beyond ICTs, on export and import activities of SMEs. To this end, a multidimensional digitalization index is constructed to capture the digital transformation in a more comprehensive way. Second, this thesis explores how DTs affect firms' labor demand. Chapter 3

[2] https://digital-strategy.ec.europa.eu/en/policies/desi-spain

[3] This chapter has been published as Añón Higón, D., and Bonvin, D. (2022). Information and communication technologies and firms' export performance. *Industrial and Corporate Change,* 31(4): 955-979.

aims to provide evidence on this issue, by studying how the extent of digitalization, measured by the index built in the previous chapter, affects firms' employment. In all chapters, data for the analysis are drawn from the Spanish Survey on Business Strategies (ESEE), which is an annual panel database conducted since 1990 and that is representative of the population of Spanish manufacturing firms with ten or more employees. It is sponsored by the Spanish Ministry of Industry, Tourism and Trade and managed by the SEPI Foundation. The ESEE provides information on firms' strategies, i.e., the decisions that firms make concerning their competitors. The questionnaire covers information on firm's activity, products and manufacturing processes, customers and suppliers, costs and prices, markets, accounting data, and for the aims of this research information on technological activities, foreign trade, and employment.

The motivation to study the impact of digitalization on trade activities as the first topic of this thesis stems from the fact that DTs are currently reshaping our economy and businesses, in particular. The diffusion of DTs has been an advance towards globalization. Digitalization has enabled the reduction of trade barriers by lowering the costs of trade and this through different channels (Venables, 2001). Previous to the ICT revolution and, more specifically, the invention of the Internet, connecting a seller and a buyer that were hundreds, or even thousands of kilometers apart, was not straightforward. With the universalization of the Internet, information about a product is often available on firms' website and this allows to easily match a seller and a buyer and promotes a shift from local trade towards global trade. E-commerce platforms, such as Amazon or Alibaba, have accelerated this phenomenon even further.

DTs also help to reduce the costs of moving merchandises. The transportation costs of moving freight have been lowered drastically due to technological progress. Moreover, some activities haven been codified and digitalized, enabling them to be moved at very low costs, reducing shipping distance and thus decreasing shipping costs. With the diffusion of ICTs and other DTs, part of the economy has become weightless. For instance, call centers allow the customer and a firm representative to communicate while being apart. Moreover, organizational changes induced by the deployment of DTs have led to further reducing distance between buyers and sellers by decreasing the costs of moving inputs and outputs.

In addition, DTs help to reduce management and monitoring costs. With the growth of Foreign Direct Investment (FDI) and outsourcing, the fragmentation of the production process has increased considerably. Indeed, intermediate inputs can be outsourced in order to reduce labor costs, which has created new management and monitoring challenges. Knowing that some activities can be codified, ICTs can be of great use in managing the production process remotely and thus it allows firms to reallocate some of their activities where wages are lower. Naturally, some exchanges require face-to-face interactions, but the new DTs support easier monitoring and management from distance, and therefore reduce the costs associated to these tasks and results in significant efficiency gains.

In light of the above arguments, we argue that the use of ICTs and other DTs can have a positive impact on the trade decisions of firms. Testing this assumption will have significant policy implications. Despite the increase in the export base since the Great Recession, Spain, our country of analysis, continues to have a relatively small base in comparison to the EU average. Therefore, it will be interesting to assess if it can be expanded by promoting DTs technologies in general, and ICTs in particular. In fact, in 2017, nearly 5% of the total number of firms in Spain were exporters, whereas this proportion was almost four times higher for the EU average. Moreover, less than 5% of Spanish SMEs engage in export activities, while more than 60% of large firms are exporters (Chacón and Machuca, 2019).

In Chapter 1, we first focus on ICTs and their role in the export activities of Spanish firms. The analysis proceeds using firm-level data drawn from the ESEE, which provides information on Spanish manufacturing firms between 1990 and 2014. For our variable of interest, namely, the use of ICT applications, information is only available since 2000, which is why the period of analysis in Chapter 1 spans from 2000 to 2014. In this first chapter, to measure the use of ICTs we consider the answers to the following questions in the survey: whether firms have a website; whether they sell online to other firms or final consumers; and whether they purchase goods or services online. A firm is considered to be an ICT user if it answers positively to any of the previous questions. This information, coupled with information on whether the firm is an exporter or not, will enable us to study the relationship between ICT use and exports propensity (the probability of exporting) by using a random effects (RE) dynamic probit model. We also explore the impact of ICT use on exports intensity (the share of foreign sales) using a dynamic Tobit II-Heckman model. Moreover, the effect of ICT on exports is broken down into two distinct effects, a direct and indirect effect. The former is simply the demand-scale effect of using ICT on the probability to export, while the latter is the effect of ICT on exports through total factor productivity (TFP). By using an endogenous Markov process, we allow ICT to impact productivity. Note that for the indirect effect to be significant, ICT must have a significant and positive impact on TFP and the same condition must hold for the effect of TFP on exports.

The findings in Chapter 1 reveal that firms that use ICT, and in particular those that have a website, experience a direct increase in their probability of exporting, but not in their export intensity. Nevertheless, ICT increases export intensity indirectly through the productivity channel. Our results are, however, subject to substantial heterogeneity, and vary depending on firm size and the sector in which the firm operates. Thus, the direct effect of ICT on export participation is positive for SMEs and non-existent for large firms. However, in terms of exports intensity, both SMEs and large firms benefit from the indirect productivity enhancement. Concerning the level of digitalization, the role of ICT is very different in whether we regard low- or high-digitalized industries. ICT positively impacts exports participation for firms in low-digitalized industries while it has no effect for their counterparts in highly digitalized industries. On the contrary, when looking at export intensity, ICT has influence both directly and indirectly on firms in highly digitalized industries.

Chapter 1 reveals that SMEs have more to gain from the use of ICTs. This coupled with the fact that they face more barriers to entering foreign markets, is the reason why in Chapter 2, we focus solely on this type of firms. Here, instead of considering only ICTs we extend the analysis to consider other dimensions of the digital transformation. Therefore, using also the ESEE, in Chapter 2 we construct a multidimensional index of digitalization following Calvino *et al.* (2018) with the aim to better capture this complex phenomenon. This index englobes a total of 13 different components representing four dimensions of the digital transformation. These dimensions are the technological components, the digital-related human capital, the extent of automation, and the way digitalization changes the way firms interact with their stakeholders. In Chapter 2, we aim to assess the direct and indirect (through TFP) impact of digitalization not only on the decision of exporting but also of importing. To evaluate the causal impact of digitalization we use a control function approach in a dynamic random effects biprobit model, which considers that both the export and import decisions are simultaneously determined.

The findings in Chapter 2 show that digitalization directly facilitates both export and import participation. Moreover, our results also provide evidence of an indirect effect of digitalization through productivity on the decision to trade. The direct effect appears to be larger for exports than for imports, while this observation is reversed when considering the indirect effect. The results in this study are also, subject to heterogeneity. Interestingly, firms belonging to low-digitalized industries seem to benefit more from digitalization than their counterparts belonging to high-digitalized industries. Firms in low-digitalized industries, thanks to DTs are able to acquire a comparative advantage in comparison to firms not adopting DTs. Finally, in order to distinguish between two different types of technologies, we disentangle the digitalization index into two sub-indices, the ICT index and the automation index. ICT technologies are likely to fragment the production process by reducing some costs associated with the physical distance and thus increase trade. Automation technologies are able to replace humans in their jobs, reshore some tasks that had previously been outsourced and therefore reduce trade. The results we obtain in this chapter tend to confirm this intuition. Indeed, the ICT index has a positive and significant direct effect on the probability to export and import, whereas automation has no impact.

However, this digital transformation also raises concerns on the automation of jobs and the potential increase of unemployment. This causes a very tangible fear among employees whose jobs are threatened by DTs and thus constitutes an important social issue. Having observed the increase in demand and in efficiency due to the adoption of DTs from previous chapters, our objective in Chapter 3 is to answer whether digitalization indeed reduces employment for the specific case of Spanish manufacturing firms.

Not only is there a lack of consensus in academic research on this issue, but this debate is also omnipresent in the news and in public opinion. The introduction of new technologies is potentially disruptive for human occupations, as some are likely to be replaced by machines. However, this potential replacement creates new tasks in which humans are needed. This is what Schumpeter (2013) describes as creative destruction. Nevertheless, technologies such as ICTs and robots have the capacity to be more disruptive, as they can perform tasks requiring human abilities, which is why robotization is such a controversial subject. As we will see in more detail in Chapter 3, the results on the effect of digitalization on employment are rather mixed. There does not appear to be a general consensus, and the results may differ depending on whether we consider skilled workers, unskilled workers, or manufacturing workers, for instance. Even among studies using the ESEE dataset, the results can be quite different (Camiña *et al.*, 2020; Stapleton and Webb, 2020; Koch *et al.*, 2021).

In Chapter 3, we examine the effect of digitalization on firms' labor demand. To this end, we use the ESEE dataset, and drawn on the digitalization index constructed in the previous chapter. In order to allow for imperfect competition and for profit-maximizing firms, we follow the framework of Ortiz and Salas Fumás (2020) and therefore consider market power in the estimation of our model. We argue that digitalization can affect employment through three different channels: the demand-scale effect, the potential replacement effect, and the productivity effect. The demand-scale effect is induced by the demand expansion power of digitalization, which enables firms to reach more buyers and expand their market, as previously shown in previous chapters. However, digitalization, and more specifically automation technologies, can also replace humans in their tasks. This is what is referred to as the potential replacement effect. Finally, through the productivity effect, DTs allow firms to organize their production more efficiently, increase their productivity and thus raise the demand for labor. In our analysis, however, due to the lack of data on asset prices, we cannot dissociate the potential replacement effect from the demand-scale effect. This implies that we are only able to identify a combination of these two effects, which we refer as the direct effect of digitalization, and estimate which one dominates by observing the sign of the coefficient.

The findings in Chapter 3 show a positive direct effect as well as a productivity effect of digitalization on firms' labor demand. Moreover, this effect persists when considering the demand for high-skilled, low-skilled or manufacturing workers, implying that the creation of tasks outweighs their destruction. However, when we analyze shares rather than absolute values, the results show important differences. Thus, the share of low-skilled and manufacturing workers is negatively affected by digitalization, contrary to the share of high-skilled workers, providing evidence in favor of the technological change bias towards high-skilled labor. Indeed, DTs create new tasks regardless of the level of skills, but skilled jobs account for a larger share of total new jobs created than unskilled jobs.

Furthermore, this could raise concerns on potential inequalities caused by wage disparities. Finally, as in Chapter 2, we disentangle the digitalization index into two sub-indices, the automation index and the ICT index to capture the potential distinct impact of these technologies. While ICTs affect the demand for labor, automation has no significant impact. This is consistent with the fact that ICTs are more likely to complement workers and automation technologies tend to replace them.

The contributions to the literature throughout this thesis are manifold. First, in all the chapters, we estimate not only the direct impact of digitalization on firm performance (i.e., trade or employment), but also the indirect effect via productivity. In this perspective, we allow digitalization (or ICT) to affect future productivity using an endogenous Markov process. Second, in Chapters 1 and 2, we model foreign market participation using a dynamic model to account for previous trade experiences. Third, in Chapter 2, we estimate the decisions to export and import simultaneously in order to examine the interdependence of these two activities. Fourth, in this chapter we introduce the digitalization index, which is one of the main contributions of this thesis as it is, to our knowledge, the first study to build an index representing the digitalization transformation of Spanish manufacturing firms. This digitalization index, which we also use in Chapter 3, englobes several dimensions of the digital transformation and allows us to capture this phenomenon in a more complete way than using isolated indicators of the phenomenon. Finally, in Chapter 3, we follow the framework of Ortiz and Salas Fumás (2020) and consider profit-maximizing firms. This implies to estimate a demand for labor that also depends on product demand factors, and hence market power, which are not relevant under the standard cost-minimization approach.

The remaining of this thesis is structured as follows. Chapter 1 examines the effect of information and communication technologies on firms' export performance. Chapter 2 focuses on trade and the digital transformation of SMEs and Chapter 3 analyses the relationship between digitalization and employment in Spanish manufacturing firms. Finally, the last section of the thesis concludes by discussing the main findings and their implications for practice, policy and future research. References and appendices are provided at the end of each chapter.

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Chapter 1

1.1. Introduction

The adoption and use of information and communication technologies (ICT, henceforth) represent a key source of competitiveness and growth for firms that are able to exploit them (Jorgenson *et al.*, 2000). In recent years, most developed economies have witnessed an expansion in the involvement of ICT in the process of production and distribution of goods and services (Alcácer *et al.*, 2016). While most studies have focused on the role of ICT in the production process (Brynjolfsson *et al.*, 2002; Cardona *et al.*, 2013), its role in trade has been mostly overlooked. Hence, in this chapter we aim at studying the relationship between firms' adoption and use of ICT and their export activity. More specifically, we examine how the use of ICT, particularly online services, can facilitate trade by focusing on both the decision of firms to export and the intensity with which they sell abroad.

The reduction of trade costs and barriers associated with the use of ICT has led to an increase in international trade flows (Yushkova, 2014). In this regard, there are several mechanisms through which ICT can lead to a reduction in trade costs (Venables, 2001). First, ICT improve market transparency, which is an essential prerequisite for exchange, thus reducing the costs of searching, matching, and communicating with different stakeholders across borders (Hagsten, 2015). Second, ICT can provide companies with additional channels for marketing and sales, enabling them to reach a larger number of digitally connected customers. Moreover, ICT enable firms to source their inputs and organize production more efficiently, leading to productivity gains (Fernandes *et al.*, 2019). ICT can also help companies to innovate and thus improve their productivity (Brynjolfsson and Saunders, 2009). This productivity gain may induce firms to export or increase their sales abroad (Bernard and Jensen, 1999).

Accordingly, we argue that there is a positive relationship between ICT and the internationalization of firms. Certainly, since DTs reduce costs and trade barriers, we claim that the use of ICT can directly induce firms to export or increase export intensity. Additionally, ICT can indirectly affect export performance through their potential enhancing effect on firms' productivity (Cardona *et* *al.*, 2013). In this regard, this study aims to provide additional insights into the relationship between ICT and export performance, by distinguishing between a direct effect through the use of ICT on export activity and an indirect effect through enhanced productivity. In doing so, data for a sample of Spanish manufacturing firms drawn from the Spanish Survey of Business Strategies (ESEE) over the period 2000-2014 will be used. Both the decision to export and the export intensity will be included in the empirical analysis. A distinguishing feature of the database is that it provides information on firms' export activities, as well as on investment in software and hardware and distinct uses of ICT. In particular, it provides information on whether the firm has a website and uses e-commerce. While having a website enables a firm to share information with potential customers, e-commerce facilitates economic transactions between sellers and buyers (Hagsten and Kotnik, 2017).

Empirical evidence on the impact of ICT on trade using micro-level data is scarce, with a few exceptions (see Añón Higón and Driffield, 2011; Fernandes *et al.*, 2019; Hagsten and Kotnik, 2017; Kneller and Timmis, 2016). Our contribution to the extant literature is twofold. First, in contrast to previous studies, in addition to the direct effect of ICT on export performance, we also analyze the indirect effect of ICT through enhanced productivity. The analysis of the indirect effect requires us to consider the links between ICT use and productivity, on the one hand, and the link between productivity and export performance, on the other. We do this by estimating in a first stage a production function in which we account for endogenous productivity gains over time from past ICT use and export experience. In a second stage, after estimating the firm's total factor productivity (hereafter, TFP), we study the effect of both ICT use and TFP on export performance. A positive estimate of the ICT variable in the export equation should be regarded as evidence of a direct effect, while a positive and significant estimate of TFP should be considered as evidence of the indirect effect of ICT through enhanced productivity. Second, instead of using a static model, we model foreign market participation as a dynamic process[4]. In this sense, our empirical analysis builds on recent literature (Brancati *et al.*, 2018; Mañez *et al.*, 2014) and tackles the issues related to the endogeneity of the lagged dependent variable and to the initial conditions problem. Moreover, the firm's export intensity is analyzed using a dynamic

[4] Although the model of Hagsten and Kotnik (2017) is dynamic in its specification, they estimate the export participation equation using a pooled probit.

type II-Tobit model and, as a robustness test, with a two-part fractional model. Finally, we explore the role that firm size and the digital intensity of the sector play in explaining the effect of ICT on exports.

Our results suggest that ICT has a direct role in the decision to export, but also has an indirect effect through productivity gains. In analyzing the facilitating role of ICT on export intensity, we find that it mainly acts through the indirect productivity channel. These effects are particularly relevant for small and medium-sized firms. Further, an interesting result emerges when distinguishing between high and low-digitized industries (Calvino *et al.*, 2018). The use of ICT does not play a direct role for firms in highly digitized industries in deciding whether or not to undertake export activities. However, it has a significant impact on export intensity. In contrast, the use of ICT in low-digitized industries enables firms to engage in export activities but does not have a significant impact on the intensity with which they sell in foreign markets, except indirectly through the productivity channel.

The rest of the chapter is organized as follows. The next section reviews the extant literature. We then describe the database and methodological approach, followed by the empirical results obtained. Last, we discuss the findings, implications, and limitations of our research.

1.2. Literature Review

The study of the relationship between ICT and exports brings together several strands of the literature on the intersection of international trade, firm dynamics, and industrial organization. First, this study contributes to the "technology gap" literature, which focuses on the role that technology in general and ICT in particular play in shaping trade (Dosi *et al.*, 1990). Studies in this tradition, building on the seminal work of Posner (1961) and subsequent empirical evidence (including Soete, 1981; Dosi *et al.*, 1990; Verspagen and Wakelin, 1997; Laursen and Meliciani, 2002, 2010), emphasize that trade flows are driven primarily by the capability to develop technological innovations and benefit from technological linkages, which represent key sources of competitive advantage, whereas cost-price factors play a limited role. These findings have been largely confirmed by country-industry level analysis, but there is also evidence at the firm-level. For example, Dosi *et al.* (2015) confirm the importance of technology over labor costs in explaining export performance for a sample of Italian firms. However, the literature on the technology gap tradition has mainly used patents and R&D to capture technological differences across trading partners, while the role of ICT has been overlooked, with the exception of Laursen and Meliciani (2010). Nonetheless, the effective deployment and use of ICT is considered an important enabler of the diffusion of knowledge and technologies (Laursen and Meliciani, 2010), and a determinant of firms' innovation outcomes (Añón Higón, 2012), which in turn are key factors for trade. It can therefore be assumed that the use of ICT plays an important role in the international competitiveness of firms.

The fact that the internet has undeniably become one of the major communication channels, and with it the use of information and communication technologies, has led many authors to broaden their interest in the potential role of ICT (or internet) in international trade. Barbero and Rodriguez-Crespo (2018) claim that the use of DTs and investments in ICT infrastructure reduce transaction costs, including the costs of entering foreign markets (Freund and Weinhold, 2004), coordination costs associated with production processes (Demirkan *et al.*, 2009), and communication and information costs (Jungmittag and Welfens, 2009). By helping firms to be better connected, ICT can enable them to improve their product offering and customize products to customer's needs.

Early empirical studies analyze the impact of ICT on trade through a gravity equation using country-level data. Freund and Weinhold (2002; 2004) provided the first evidence. In particular, Freund and Weinhold (2004), for a sample of 56 countries, find that a 10 percent increase in the relative number of web hosts in a country led to a nearly one percent higher trade in the late 1990s. Several studies followed that used only cross-sectional data. Clarke and Wallsten (2006), for example, find a positive effect of the number of internet users on trade between developing and developed countries. Similarly, Yushkova (2014) shows that the extent of internet usage positively influences exports. More recently, using a sample of 152 countries and 86 industries in 2013, Wang and Li (2017) find evidence that ICT, proxied by three indices (ICT development, subscription, and usage) facilitate exports, particularly in R&D intensive industries.

Nevertheless, cross-sectional data makes the inference of a causal relationship doubtful. Some studies have therefore used panel data to overcome this limitation. Thus, Vemuri and Siddiqi (2009) conclude that ICT infrastructure and the availability of the internet for commercial transactions have a positive effect on trade for a panel of 64 countries between 1985 and 2005. Portugal-Perez and Wilson (2012) construct a weighted ICT-based index for 101 countries between 2004 and 2007 and find that the ICT impact on exports becomes increasingly important as countries become wealthier. In the context of the technology-gap literature, Laursen and Meliciani (2010) find that ICT-related knowledge flows affect export market shares for a sample of 14 OECD countries over the period 1981-2003. All in all, and despite differences in the data and methods used, there is ample evidence at the macro level that increased capacity and use of ICT (measured in various ways) has a positive impact on trade.

While much of the above literature focuses on country-level data, firm-level studies are much rarer (see, for example, Añón Higón and Driffield, 2011; Fernandes *et al.*, 2019; Hagsten and Kotnik, 2017; Kneller and Timmis, 2016). In a cross-section setting, Añón Higón and Driffield (2011) find that ICT use is positively correlated with both export propensity and intensity for a sample of UK small and medium-sized firms (SMEs). Hagsten and Kotnik (2017), using firm-level data of 12 European countries[5], show that basic ICT tools (such as a website) are more important for exporting than more advanced ones (such as the use of broadband or e-commerce). Kneller and Timmis (2016) find a strong positive causal impact of broadband use on the propensity to export business services[6] but not for export goods in UK firms. To address the endogeneity concern, spatial differences in broadband availability (linked to the historical telephone network) are used as an instrument for firms' use of the internet. Similarly, using firm- and province-level data for Chinese firms between 1999 and 2007, Fernandes *et al.* (2019) evidence a causal positive effect of the internet rollout on manufacturing exports, even before the rise of e-commerce platforms. We contribute to this literature by also providing causal evidence that the use of ICT, and not just the internet, has a positive effect on the exports of manufacturing goods. However, whereas these studies only consider the direct effect of ICT use (or internet) on trade, we also regard the potential indirect effect of ICT through enhanced TFP. Moreover, instead of using a static model, we model both the extensive and intensive margin as a dynamic process following recent empirical evidence (Brancati *et al.*, 2018).

[5] The dataset comes from the ESSLait project, described in Hagsten (2015).
[6] The present study does not focus on services trade as we lack data on it.

1.2.1. ICT and Productivity

The analysis of the indirect impact of ICT on exports through increased productivity relates this study to an expanding literature on the impact of ICT on firm productivity. The arguments by which ICT should have strong positive effects on productivity are manifold (Syverson, 2011). ICT endows firms to source inputs and organize production more efficiently (Arvanitis and Loukis, 2009). Moreover, the use of ICT can facilitate changes in management and organizational practices (such as the introduction of *just-in-time* management) and contribute to the development of new products (Añón Higón, 2012). Thus, ICT as a general-purpose technology can enable innovation in adopting firms and lead to higher productivity (Bresnahan and Trajtenberg, 1995; Brynjolfsson and Saunders, 2009; Laursen and Meliciani, 2010). However, empirical evidence, particularly at the firm level, is rather mixed.

The first studies found limited evidence of the positive effects of ICT on productivity (for a review, see Cardona *et al.*, 2013). As these technologies became more widespread and adoption rates increased, the number of firm-level studies finding a positive significant effect on productivity increased. Brynjolfsson and Hitt (2003), using a panel of large US firms over the 1987-1994 period, find that computer spending has a positive effect on total factor productivity, and it does so more in the long-run than in the short-run. Similarly, using plant-level data in the valve manufacturing industry in the US, Bartel *et al.* (2007) show that the adoption of new ICT-enhanced machinery raises productivity, especially by reducing setup times. Bloom *et al.* (2012) show that US multinationals operating in Europe achieve higher productivity from ICT capital than non-US multinationals (or domestic firms) and that this higher return is related to the use of better management practices by US companies.

More recently, the new productivity slowdown has sparked renewed interest in the role of ICT, but again with mixed results. Acemoglu *et al.* (2014), using US firm-level data over 1977-2007, find no effect of IT intensity on productivity, except in the computer-producing industry. DeStefano *et al.* (2018) find that ADSL broadband causally affects firm size but not the productivity of UK establishments in the early 2000s. In contrast, Bartelsman *et al.* (2019) show that there is a positive relationship between the share of employees with broadband access and productivity for a sample of European firms over the period 2002-2010. Similarly, Gal *et al.* (2019) show a strong association between the adoption of DTs in a sector and productivity gains at the firm level for a large sample of OECD firms.

Departing from previous literature, we distinguish between ICT investment and ICT use. ICT investment contributes to capital-deepening and labor productivity via ICT capital, while the firm's strategic decision to use ICT endogenously affects TFP. Thus, opting for an endogenous process in the dynamics of TFP, as proposed by Doraszelski and Jaumandreu (2013) for R&D, considers the uncertainties associated with the success in using ICT and could explain the heterogeneous results of previous studies.

1.2.2. Productivity and Exports

However, for the indirect effect to be effective, TFP must have a positive and significant effect on export performance. Thus, this study also contributes to the literature on trade and productivity. Numerous studies have documented a strong positive relationship between productivity and export performance at the firm level. Two different theoretical interpretations have been proposed to explain this pattern: the self-selection hypothesis and the learning mechanisms. The self-selection hypothesis states that firms with productivity above a threshold level self-select into export markets (Melitz, 2003). In other words, only those firms that are efficient enough to overcome the sunk costs of entering foreign markets begin to export. On the other hand, learning-by-exporting (hereafter LBE) refers to the productivity gains that firms experience after entering export markets (De Loecker, 2013).

Empirically, most studies support the self-selection hypothesis (Bernard and Jensen, 1999), while the LBE hypothesis is less frequently supported. De Loecker (2013), however, argues that most previous tests for LBE may be flawed. The solution to this flaw is to allow for an endogenous productivity process in the estimation of a production function, where exports affect future productivity. As a result, studies that follow this approach find significant LBE effects (including De Loecker, 2013; Máñez *et al.*, 2015).

Although our interest lies in the impact of TFP on export performance, our model also accounts for the potential LBE effect. While most studies assume that TFP is an exogenous process, the self-selection argument raises an important question about the sources of high productivity among exporting firms (Cassiman and Golovko, 2011). How do firms achieve higher levels of productivity that enable them to enter and remain in foreign markets? We argue that the use of ICT and export experience (consistent with LBE) induce future productivity gains and thus indirectly determine firms' extensive and intensive trade margins.

1.3. Data and Descriptive Statistics

1.3.1. Data

The data used in this work come from the Survey of Business Strategies (hereafter ESEE) for the period 2000-2014. The ESSE is an annual panel database conducted since 1990. It is sponsored by the Spanish Ministry of Industry, Tourism and Trade and managed by the SEPI Foundation. It is worth noting that the ESEE is representative of Spanish manufacturing firms classified by two-digit manufacturing industries of the NACE-Rev.1 and size categories. In particular, the ESEE provides information on firms' strategies, i.e., the decisions that firms make concerning their competition. The questionnaire covers information on: firm's activity, products and manufacturing processes, customers and suppliers, costs and prices, markets, technological activities, foreign trade, and accounting data. Questions on the use of ICT have only been asked since 2000, which is why our period of analysis begins in that year.

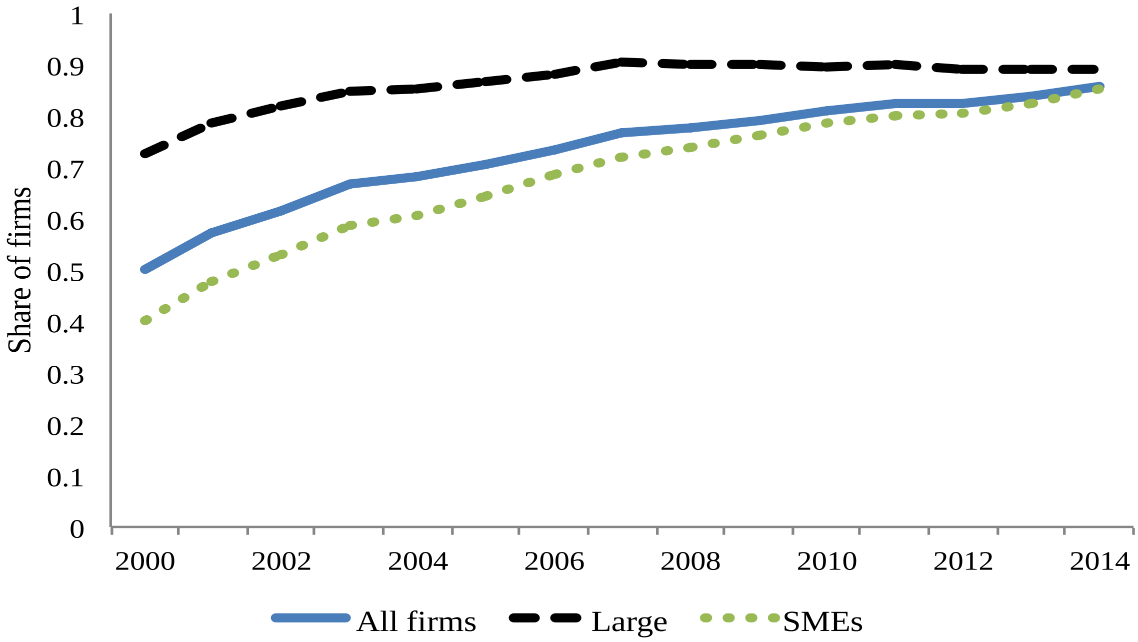
The sampling procedure of the ESEE is as follows. Firms with fewer than 10 employees were initially excluded from the survey. Firms with 10 to 200 employees were randomly sampled, holding around 5% of the population in 1990. All firms with more than 200 employees were surveyed on a census basis, with a participation rate of about 70% in 1990[7]. A major effort was made to minimize attrition and to include new firms each year with the same sampling criteria as in the base year so that the sample of firms would remain representative over time.

The initial sample consists of an unbalanced panel of about 23,975 observations, corresponding to 3,216 firms observed in at least two consecutive periods from 2000 to 2014. From this initial sample, we remove those firms that do not provide relevant information for the analysis. After cleaning the data, we end up with a sample of 17,207 observations corresponding to 2,448 firms[8].

[7] Because of this sampling procedure, we define large firms in the empirical analysis as those with more than 200 employees, instead of the usual 250 threshold. Firms with 200 or less employees (but at least with 10) are considered SMEs.
[8] Several observations are lost when we estimate total factor productivity (TFP).

As for the variables of interest, the ESEE provides information on whether the firm exports and the share of foreign sales. More specifically, for the export status of the firm, we use the following question "Indicate whether the firm exported (including exports to the European Union) this year, either directly or through other firms in the same group". In addition, the survey provides not only annual information on firms' investment in information processing equipment but also information about the firm's use of ICT. Specifically, firms are asked whether they have a website, whether they sell online to other firms or final consumers (B2B or B2C), and whether they purchase goods or services online. Firms that answer "yes" to any of these questions are considered ICT users.

Figure 1.1: Evolution of ICT users in Spain (2000-2014)



Source: ESEE survey and own elaboration

Figure 1.1 shows the evolution of ICT users in the Spanish manufacturing sector over the period 2000-2014. We observe that of all firms in 2000, 50% were ICT users, i.e., used online services. This share has increased considerably over time, and was over 85% in 2014, although the pace of growth has slowed since the 2008 crisis. The figure reveals significant differences in ICT use between small and medium-sized enterprises (SMEs) and large firms. While 75% of large firms were already using ICT in 2000, only 40% of SMEs did. However, this difference has narrowed over time, and in 2014, 89% of large firms and 85% of SMEs were using ICT. The digitalization of Spanish manufacturing SMEs has thus undergone a remarkable process in the 21st century.

1.3.2. Descriptive Statistics

We classify firms in our sample into different categories according to their size (number of employees) and sector. Thus, we distinguish between SMEs (i.e., firms with less than 200 employees) and large firms (i.e., firms with 200 or more employees), and according to whether they belong to high- (or low) digitized industries (see Table 1A.1 in the appendix). The latter classification is based on the sectoral digital intensity taxonomy proposed by Calvino *et al.* (2018). The taxonomy is based on how industries are ranked along several dimensions, including ICT investment, purchases of intermediate ICT goods and services, use of robots, number of ICT specialists, and online sales. We consider industries to be highly digitized if they are classified as medium-high or high-digitally intensive by Calvino *et al.* (2018). Table 1.1 shows the percentage of observations in the overall sample that fall into each category. SMEs account for about 72% of the observations, while larger firms account for only 28%. These percentages remain relatively constant when the total sample is divided into high- and low-digitized industries, respectively.

Table 1.1: Observations in the sample by firm size and sectors' digital intensity

	All firms		High digitalization industries		Low digitalization industries	
Size class	Observations	%	Observations	%	Observations	%
SME	12,552	72.24	4,789	71.97	7,763	73.56
Large	4,655	27.76	1,865	28.03	2,790	26.41
Total	17,207	100	6,654	100	10,553	100

Note: size class is defined in terms of the average number of employees of the firm: SME (< 200 employees) and large (>=200 employees). The distinction between high digitalization industries (resp. low digitalization industries) rests on the sectoral taxonomy of digital intensity provided by Calvino *et al.* (2018). We keep only in the sample firms which are observed at least for two consecutive years and for which an estimate of TFP can be obtained.

Table 1.2 presents descriptive statistics for the variables of interest, including export propensity and intensity, ICT-related variables, and variables reflecting the structural characteristics of firms. The average firm in the sample has nearly 200 employees and is 27 years old. 68% of the sampled firms export, and on average 22% of sales come from foreign markets. We complement the descriptive statistics by calculating the *t*-test of mean comparison, which captures the significance of different characteristics between ICT users and non-ICT users. A firm in a given year is an ICT user if it has a website or/and sells online to other firms or (domestic or international) final consumers, or/and purchases online. The results in Table 1.2 show that, on average, ICT users have a greater propensity to export (77% of ICT users export) and a higher export intensity (25% of their sales come from exports) than non-ICT users. This supports our hypothesis that ICT use can facilitate foreign trade. Moreover, the *t*-test results in Table 1.2 show that, on average, ICT users are larger (employing more than 225 people on average), older (29 years), and more engaged in R&D (43% conduct R&D) compared to non-ICT users; however, they are not statistically more productive in terms of TFP.

Table 1.2: Descriptive statistics for all firms and ICT users

	All firms				**ICT users**		**ICT vs. non-ICT users**
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**t-test[1]**
Export participation	0.68	0.46	0.0	1.0	0.77	0.42	42.55***
Export intensity	0.22	0.28	0.0	1.0	0.25	0.29	24.27***
ICT user	0.76	0.43	0.0	1.0	1.00	0.00	
Website user	0.76	0.43	0.0	1.0	1.00	0.00	
Online trader	0.32	0.47	0.0	1.0	0.42	0.49	55.12***
R&D propensity	0.37	0.48	0.0	1.0	0.43	0.50	29.51***
Human capital	6.46	8.27	0.0	100.0	7.35	8.75	25.69***
Age (*in logs*)	3.30	0.66	0.7	5.2	3.37	0.64	19.49***
Size	199.95	487.43	1.0	15,003	225.11	515.16	12.07***
TFP (*in logs*)	3.68	1.46	1.8	8.3	3.67	1.45	-1.57
Foreign capital	0.18	0.39	0.0	1.0	0.20	0.40	6.73***
Appropriability	0.04	0.19	0.0	1.0	0.04	0.21	9.35***
Recessive market	0.30	0.46	0.0	1.0	0.31	0.46	6.34***
Expansive market	0.21	0.41	0.0	1.0	0.22	0.42	5.43***
Competitors	0.55	0.50	0.0	1.0	0.57	0.49	9.18***
External Finance	4.26	3.41	2.0	10.0	4.45	3.51	13.25***
Internal Finance	6.04	2.39	2.0	10.0	6.10	2.37	5.68***
Observations	17,207				13,062		

Source: ESEE 2000-2014. The sample are firms which are at least observed for two consecutive years and for which an estimate of TFP can be obtained.
Note: [1] t-values for two-sample t-test with equal variance: mean(ICT user) – mean(non-ICT user); *** significant at 1% level.

1.4. Methodology

To analyze how the use of ICT affects firms' exports, we estimate two different models. The first looks at the impact of ICT on the *extensive margin* of exports, i.e., the propensity to export, while the second examines how ICT affects the *intensive margin*, measured by the share of foreign sales in total sales.

1.4.1. The Export Extensive Margin and ICT

The model used to estimate the direct and indirect effects of ICT use on the propensity to export is based on the Roberts and Tybout (1997) model. Accordingly, firms decide to export when current and expected revenues exceed current costs, including sunk entry costs that are captured by the previous export status. This implies the use of a dynamic specification to model export participation. This specification is also consistent with the evolutionary economics approach (Nelson and Winter, 1982), since the previous export status may also capture accumulated experience in export markets reinforcing firms' competitiveness (Laursen and Meliciani, 2002). Thus, we assume that firm *i* decides to export in period *t* if the expected present value of profits from exporting is positive. Formally,

$$DEXP_{it}^{*} = \alpha_i + \delta_1 ICT_{it-1} + \delta_2 TFP_{it-1} + \eta DEXP_{it-1} + x'_{it-1}\theta + d_j + d_t + \varepsilon_{it} \tag{1.1}$$

$$DEXP_{it} = 1[DEXP_{it}^{*} > 0] \tag{1.2}$$

where $DEXP_{it}^{*}$ is a latent variable representing the unobserved profitability of exporting. However, instead of observing $DEXP_{it}^{*}$, we observe a binary variable ($DEXP_{it}$) that indicates the sign of the latent variable. Thus, 1[.] is an indicator function that takes the value of one when firm *i* exports at period *t* and zero otherwise. In equation (1.1), ICT_{it-1} is the firm's ICT use and TFP_{it-1} stands for the firm's TFP, which controls for the indirect effect of ICT. Then, after controlling for the indirect effect, the parameter δ_1 informs about the direct effect of ICT on the propensity to export. $DEXP_{it-1}$ is a dummy accounting for the previous export status and proxies for the existence of sunk costs and learning effects. We also account for a vector of other lagged explanatory variables[9], represented by x_{it-1}. Besides, α_i represents

[9] Table 1A.2 in the Appendix presents the definition of variables.

the unobserved firm-specific effect, d_j denotes industry fixed effects at the two-digit level and d_t are time effects. The effect of other time- and firm-specific unobservable determinants is summarized in the error term, ε_{it}.

Included in x_{it-1} are a set of firm characteristics that have been considered as factors influencing the export decision in previous literature (Añón Higón and Driffield, 2011; Brancati *et al.*, 2018; Mañez *et al.*, 2014). In particular, we control for the firm's internal and external financial resources. Studies that focus on the role of financial factors show that liquidity constrained firms face more difficulties in exporting (Wagner, 2014). In this study, we use a multivariate financial index to proxy both internal and external finance (see Appendix B for details). We also control for the firm's age, R&D, size (measured by the number of employees), human capital, foreign capital participation, appropriability conditions, firm's cycle (measured as the firm's assessment of whether the demand in its main market is recessive or expansive), and market competitors. To avoid potential simultaneity bias, all explanatory variables enter with one lag in the model specification.

A concern in the estimation of equation (1.1) is the bias due to the initial condition problem (Heckman, 1981) and the potential correlation between the unobserved heterogeneity term[10] (i.e., α_i) and the covariates. To simultaneously deal with these issues, we follow Wooldridge (2005) who suggests modeling the unobserved heterogeneity as a function of the initial condition, $DEXP_{i0}$, and other covariates, and adopting a conditional maximum likelihood approach. Hence, we model α_i as:

$$\alpha_i = \delta_0 + \delta_1 \overline{q_i} + \delta_2 DEXP_{i0} + \upsilon_i \tag{1.3}$$

where υ_i is assumed to be normally distributed and independent of the initial conditions, the explanatory variables, and the error term (ε_{it}). The vector $\overline{q_i}$ contains the within-means of the control variables that are likely to be correlated with α_i, i.e., the Mundlak-Chamberlain means (Chamberlain, 1982; Mundlak, 1978). In this regard, we follow Semykina (2018) and assume in the baseline specification that the unobserved individual effects are only correlated with the firm's internal and external financial

[10] We adopt a random effects model. Since the model is nonlinear, the standard fixed effect panel method would produce inconsistent estimators (Semykina, 2018).

constraints and the appropriability conditions. In the present context, the within-means can be interpreted as measures of the firm's financial stability, which can also be viewed as proxies for unobserved firm-specific characteristics (e.g., management quality). We will also consider a specification including the within-means of all exogenous variables in *x*, as a robustness check.

1.4.1.1. Modeling the Indirect Effect of ICT Through TFP

The starting point for analyzing the indirect effect of ICT on export performance is to estimate TFP. The traditional approach to study the role of ICT in productivity is to estimate a production function in which total capital is split into ICT capital and non-ICT capital[11] (Bloom *et al.*, 2012; Cardona *et al.*, 2013). We also follow this approach, but additionally argue that it is the use of ICT and not the investment that leads to TFP gains. We thus distinguish between investment and usage. While ICT investment contributes, through ICT capital, to capital-deepening and labor productivity, the use of ICT enables firms to source their inputs more efficiently and to innovate, serving as a general-purpose technology (Bresnahan and Trajtenberg, 1995; Tambe and Hitt, 2014). We therefore proceed to estimate the following Cobb-Douglas production function:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + \omega_{it} + e_{it} \tag{1.4}$$

where we denote the logarithm of real gross output, labor, non-ICT physical capital, ICT capital, and materials as y_{it}, l_{it}, k_{it}^{NIT}, k_{it}^{IT}, and m_{it}, respectively. Also, ω_{it} is the firm's productivity (i.e., TFP), and e_{it} is an *i.i.d.* error term.

Accounting for the potential role of ICT use in enhancing future productivity involves departing from the standard approach of considering an exogenous Markov process for the productivity dynamics (Olley and Pakes, 1996). Instead, in the spirit of Doraszelski and Jaumandreu (2013), we assume that productivity follows a first-order endogenous Markov process that depends on the firm's ICT use and a

[11] If the estimated output elasticity of ICT capital is found to exceed its factor share, this is interpreted as evidence of excess returns, and hence that ICT capital contributes to TFP growth (Cardona *et al.*, 2013).

random shock. Moreover, we assume that export experience also influences the productivity dynamics (see De Loecker, 2013):

$$\omega_{it} = f(\omega_{it-1}; DEXP_{it-1}; ICT_{it-1}) + \xi_{it} \quad (1.5)$$

where *f(.)* is an unknown function, and ξ_{it} is an unexpected innovation shock. This shock represents uncertainties associated to productivity, uncertainties inherent in the use of ICT, such as the success in its implementation, and those related to the internationalization process (Doraszelski and Jaumandreu, 2013). By including lagged productivity in the Markov process, we control for productivity differences that may have existed before the start of exporting or before the adoption of ICT. In this way, we account for potential self-selection. Further, using an endogenous productivity process allows us to control for learning effects. In this way, we account for the potential role that both the firm's prior export experience, which captures "the learning by exporting effect", and prior ICT use can play in shaping productivity.

The discussion now turns to the estimation process. Estimating equation (1.4) by OLS leads to biased and inconsistent estimates because the firm's choice of inputs depends on its productivity, ω_{it} (which is observed by the firm but not by the econometrician). To address this problem, we implement the control function approach pioneered by Olley and Pakes (1996), and apply the GMM estimation proposed by Wooldridge (2009)[12]. In doing so, we assume that the demand for materials is a function of firms' ICT, non-ICT capital, and productivity. Also, such demand is monotonic and strictly increasing in productivity, and, under certain conditions, it can be inverted to obtain: $\omega_{it} = m_t^{-1}(k_{it}^{IT}, k_{it}^{NIT}, m_{it}) = h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it})$. Then, substituting into (1.4) we get the first equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it}) + e_{it} \quad (1.6)$$

[12] The method distinguishes between state variables, in our case both types of capital, and flexible variables, here labor and materials. The realization of the state variables in period *t* is decided based on the information in *t-1*, and thus they are not affected by the productivity shock arriving *t*, while flexible variables are determined in response to the shock.

Since $h_t(.)$ is an unknown function proxied by a higher degree polynomial, the identification of the capital and materials coefficients requires of an additional equation that deals with the dynamics of productivity. This equation is the first-order endogenous Markov process described by (1.5). Considering that $\omega_{it} = h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it})$, equation (1.5) can be rewritten as $\omega_{it} = f(h_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}), DEXP_{it-1}, ICT_{it-1}) + \xi_{it} = g_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DEXP_{it-1}, ICT_{it-1}) + \xi_{it}$; and plugging this expression into (1.4) we obtain the second equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + g_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DEXP_{it-1}, ICT_{it-1}) + u_{it} \quad (1.7)$$

where $g_t(.)$ is an unknown function proxied by a higher degree polynomial, and $u_{it} = \xi_{it} + e_{it}$ is a composed error term.

Then, equations (1.6) and (1.7) are estimated jointly by GMM (Wooldridge, 2009) using the appropriate instruments[13]. As a result, we obtain both output elasticity and the firm-specific TFP estimates, the latter obtained as residuals. Table 1A.3 in the Appendix reports the estimates of the output elasticities for 10 manufacturing industries classified as in Doraszelski and Jaumandreu (2013). The results show that the output elasticity of ICT capital is significant for all industries except for the non-metallic minerals industry, and it ranges from 0.009 in the metals and metal products industry, the food industry, and the textile industry to 0.037 in the electrical goods industry.

Once the estimated TFP is obtained for each industry, the resulting distribution is winsorized at the 1st and 99th percentiles to control for the impact of outliers. The TFP is then included as a regressor in the export propensity and intensity equations. However, we should notice that for ICT use to have an indirect effect through TFP on export performance, two conditions should be met. First, ICT should have a significant effect on productivity; and, second, the coefficient of TFP in the equations describing

[13] We follow Doraszelski and Jaumandreu (2013) and De Loecker (2013) and do not account for sample selection by modelling a firm's exit decision.

the extensive and intensive margin should be positive and significant. To check the first condition, we consider a linear specification of the Markov process described by equation (1.5):

$$\omega_{it} = \beta_1\omega_{it-1} + \beta_2 ICT_{it-1} + \beta_3 DEXP_{it-1} + \gamma' z_{it-1} + \alpha_j + \alpha_t + \alpha_i + \epsilon_{it} \quad (1.8)$$

where the firm's TFP (ω_{it}) is a function of its lag value (ω_{it-1}), the prior ICT use, and the prior export status. In addition, we control for other factors that may influence the evolution of productivity, including a vector of observed firm characteristics[14] (z_{it-1}), sector dummies (α_j), year dummies (α_t), and firm fixed effects (α_i). We interpret positive and significant estimates of β_2 as evidence of enhancing TFP effects from ICT use. Equation (1.8) is estimated by the two-step system-GMM estimator for dynamic models (Arellano and Bover, 1995; Blundell and Bond, 1998), which accounts for unobserved heterogeneity and the endogeneity bias[15].

1.4.2. The Intensive Margin of Exports and ICT

In this section, we delve into the relationship between ICT and export intensity. Modeling the intensive margin needs to consider the non-random selection that leads some firms to export, which is consistent with the self-selection hypothesis. To this end, we estimate a dynamic Type II-Tobit model with the Heckman two-stage procedure, which allows for the two processes, the selection into exports and the intensity, to be correlated (see Heckman, 1979). The identification of the model requires an exclusion restriction, i.e., at least one factor should be identified that influences export participation but not export intensity. We use the previous export status as the exclusion restriction on the grounds that it is a proxy for sunk costs of entering foreign markets and therefore only affects the extensive margin (see Brancati *et al.*, 2018). Hence, the selection process is specified as described in equations (1.1) and (1.2), while the intensive margin (*EXI*) is modeled as follows:

[14] We control for firm size and firm age.

[15] All the specifications provide suitable results for the Hansen test of overidentifying restrictions (testing for instruments validity) and for the non-serial correlation of the error terms.

$$EXI_{it} = \begin{cases} \beta_i + \zeta_1 ICT_{it-1} + \zeta_2 TFP_{it-1} + x_{it-1}\theta + \rho EXI_{it-1} + d_j + d_t + \vartheta_{it}, & if \;\; DEXP_{it} = 1 \\ 0, & otherwise \end{cases} \tag{1.9}$$

In equation (1.9), the parameter ζ_1 informs about the direct effect of ICT on the export intensity, while the parameter ζ_2 informs about the indirect effect accruing through the TFP channel, conditional on ICT use affecting TFP. However, the consistency of the Type II-Tobit crucially depends on the assumptions of normality and homoscedasticity. Therefore, as a robustness check, we also present results from a generalized two-part fractional model (Wulff, 2019). Here, we model the selection equation (export participation) with a random effects probit model and the export-to-sales ratio with a Generalized Linear Model (GLM), which may be more appropriate when the dependent variable is a share, as in the case of the export intensity (Papke and Wooldridge, 2008)[16].

1.5. Results

1.5.1. Extensive Margin Model

We now turn to assess the direct and indirect effects of ICT on the extensive margin, i.e., on the export decision. We will consider the direct effect attributed to ICT once we control for the indirect effect through TFP. As mentioned above, two conditions must be met for the indirect effect to occur: first, ICT must have a significant effect on TFP, and second, the coefficient of TFP in the export participation equation must be positive and significant. Thus, our starting point for analyzing the possible indirect effect is the endogenous Markov process described in equation (1.8). The results of estimating this equation are presented in Table 1.3. Although the definitive evidence for the indirect effect is provided below, the results presented here confirm the effect of ICT use on TFP. First, results in column (1) show that the coefficient of ICT is positive and significant, which supports the assumption that ICT use enhances future TFP. In column (2), we break down the effect of ICT use into two distinct digital capabilities of the firm: the use of a website and conducting online transactions. In this way, we potentially capture the effect of a basic digital capability represented by the use of a website, and a more

[16] To estimate the generalized two-part fractional model, we use the conditional mixed-process framework implemented by the *cmp* Stata command (Roodman, 2011).

advanced capability represented by the use of e-commerce (Hagsten and Kotnik, 2017). We find that the use of basic ICT applications increases TFP, but the use of more advanced technologies, such as online trade, has no significant effect on TFP. It might be that the large adjustment costs associated with implementing online trading platforms outweigh the potential gains. In contrast, the demand-enhancing effects coupled with relatively low setup and maintenance costs of websites result in significant productivity gains for the average firm. The results presented in columns (3) and (4) also provide evidence of the impact of ICT use on the growth rate of TFP. Moreover, the coefficient of *DEXP* is positive and significant in all specifications, suggesting the presence of learning-by-exporting effects, as in De Loecker (2013). In summary, the evidence presented in Table 1.3 suggests that firms that use ICT develop capabilities that enable them to improve their productivity, so the first condition for the presence of the indirect effect is satisfied. The estimation of equation (1.1) will provide the final proof.

Table 1.3: ICT use and TFP

Dependent variable:	TFP (1)	TFP (2)	TFP growth (3)	TFP growth (4)
TFP in *t*-1	0.885***	0.849***	-0.141**	-0.132***
	(0.053)	(0.050)	(0.055)	(0.051)
ICT	0.018**		0.023***	
	(0.009)		(0.009)	
Website user		0.018**		0.015*
		(0.008)		(0.008)
Online transactions		0.005		0.005
		(0.005)		(0.005)
DEXP	0.056***	0.037*	0.059***	0.038*
	(0.022)	(0.019)	(0.022)	(0.021)
Size	0.001	0.002	0.003	0.001
	(0.009)	(0.012)	(0.010)	(0.010)
Age	-0.005	0.000	-0.004	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.319**	0.413***	0.388**	0.361***
	(0.145)	(0.136)	(0.151)	(0.137)
Hansen test	130.51	223.08	133.78	174.17
[p-value]	[0.422]	[0.126]	[0.345]	[0.297]
Observations	16,022	16,022	16,022	16,022
Firms	2,414	2,414	2,414	2,414

Notes: The dependent variable in (1) and (2) is the log of TFP; while in (3) and (4) is the difference in the log of TFP from *t*-1 to *t*. All explanatory variables are included with one-period lag. All specifications include industry and year dummies. Estimates are obtained through the two-step system GMM estimator. We use levels of TFP and size dated (*t*-3) and (*t*-4) as well as ICT use and exports dated (*t*-3) as instruments in the difference equation, and differences dated (*t*-2) as instruments in the levels equation, as well as age, year and industry dummies.

Table 1.4 presents the results of estimating equation (1.1) under different specifications. The results are presented in terms of average marginal effects and the respective standard errors. The fact that TFP is an estimated regressor could render the standard errors inaccurate and thus affect inference. To address this issue, we report block bootstrapped standard errors based on 500 replications, where the firm is the block unit. Although not reported, all specifications also control for sector dummies at the two-digit level capturing different technological opportunities and other unobserved factors that vary across industries, and time dummies capturing business cycle effects.

As a benchmark, column (1) reports the OLS estimates where the dependent variable is treated as continuous. Since the conditional probability may lie outside the interval [0, 1], the resulting estimator is generally inconsistent. To overcome this issue, a pooled probit (column (2)) is estimated that, however, does not account for unobserved heterogeneity. For this reason, the results of a random effects probit model that accounts for unobserved heterogeneity, the initial condition, and Mundlak means are presented in columns (3) and (4). A likelihood ratio test reveals that unobserved heterogeneity is key in explaining export participation and that the random effects probit model is preferable to the pooled probit model. Consequently, we focus on the last two columns of the table. In column (3), we include the ICT user dummy while in column (4), we break down the effect of ICT use into a basic digital capability represented by the use of a website, and a more advanced capability represented by the use of e-commerce.

Concerning the direct effect, we find that ICT use has a positive and significant direct impact on the probability of exporting. This mirrors findings of the technology gap literature, according to which technology, in this case ICT, stands as a crucial dimension that enables firms to participate in foreign markets. This result is also consistent with the view that ICT use contributes to the development of new or better quality goods capable of attracting foreign demand. Comparing the models with different types of ICT use, we find that the effect of ICT on export propensity is due to the use of a website and not to the use of online transactions. E-commerce activities indeed seem to have a positive but insignificant effect on the export decision once we control for website presence. This goes in line with the findings of Hagsten (2015) and Hagsten and Kotnik (2017), who also find that it is mainly basic ICT capabilities such as owning a website that are related to the decision to export. The direct effect of using ICT, or simply having a website, is to increase the probability of exporting by two percentage points, holding all other variables constant. Thus, the use of a website facilitates access to new foreign customers by reducing entry-related costs, and by providing firms with new channels of information, marketing and sales.

Table 1.4: The effect of ICT-use on export participation. Marginal effects

	OLS	Probit	RE Probit	RE Probit
	(1)	(2)	(3)	(4)
Lag Export participation	0.860***	0.263***	0.178***	0.178***
	(0.007)	(0.005)	(0.009)	(0.009)
ICT	0.030***	0.022***	0.020***	
	(0.004)	(0.004)	(0.005)	
Website user				0.020***
				(0.005)
Online transactions				0.001
				(0.005)
TFP	0.034***	0.025***	0.030***	0.030***
	(0.007)	(0.007)	(0.011)	(0.011)
R&D	0.023***	0.026***	0.024***	0.024***
	(0.004)	(0.004)	(0.006)	(0.006)
Human capital	0.000	0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.005*	0.005*	0.003	0.003
	(0.003)	(0.003)	(0.004)	(0.004)
Size	0.003	0.017**	0.010	0.010
	(0.002)	(0.007)	(0.025)	(0.025)
Foreign capital	0.019***	0.028***	0.029***	0.029***
	(0.004)	(0.006)	(0.010)	(0.010)
Appropriability	0.021***	0.031**	0.022	0.022
	(0.008)	(0.012)	(0.015)	(0.015)
Recessive market	-0.001	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.005)	(0.005)
Expansive market	0.010**	0.010**	0.013**	0.013**
	(0.004)	(0.004)	(0.005)	(0.005)
Competitors	0.002	0.001	-0.003	-0.003
	(0.003)	(0.003)	(0.005)	(0.005)
External Finance	0.001**	0.001***	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Internal Finance	-0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Time & industry FE	Yes	Yes	Yes	Yes
Initial condition			Yes	Yes
Mundlak means			Yes	Yes
Observations	14,932	14,932	14,932	14,932

Notes: We report marginal effects at sample means. All specifications include industry and year dummies. All explanatory variables are included with one-period lag. Specifications in columns (3) and (4) include the initial condition and the within-means of appropriability, internal and external finance, which appear statistically significant. Block bootstrapped standard errors at firm level in parentheses (500 replications). * Significant at 10%, ** significant at 5%, *** significant at 1%.

Regarding the indirect effect, the results in Table 1.4 show that TFP has a positive and significant effect on export participation, which implies that the second condition for the existence of the indirect effect is met. Thus, considering the results in Table 1.3 and 1.4 together, we can infer that ICT increases the probability of selling in foreign markets not only through a direct channel but also through productivity gains (the indirect TFP channel). More productive firms are more likely to export as they are able to bear the entry sunk cost and survive in competitive foreign markets. This result is in line with Mañez *et al.* (2015), who also find a positive effect of TFP on the export decision in Spanish firms. Moreover, our results show that both the direct and indirect effects stem from the use of basic ICT solutions, such as the use of a website.

As expected, past export experience stands as an important determinant of actual export propensity, suggesting that the export behavior is persistent. All else being equal, firms that export in period *t*-1 are about 18 percentage points more likely to continue exporting in period *t* compared to non-exporters. This evidence of persistence in exporting might be attributed to both, the presence of sunk entry costs, but also to learning effects due to the accumulation of market experience, which increases firms′ profitability over time and allows them to continue exporting[17] (Timoshenko, 2015).

As for the other control variables, the results in Table 1.4 show that, ceteris paribus, firms that conduct R&D activities are two percentage points more likely to export, which is similar to the direct effect of ICT. R&D reflects firms' scientific and technological capabilities beyond ICT, which previous studies have found to be directly related to the development of comparative advantages in trade (Verspagen and Wakelin, 1997). Consistent also with previous studies, foreign-owned firms are also more likely to export. Further, the expansion state of demand is an important factor influencing the decision to export, with the expected positive sign (see Cassiman and Golovko, 2011). Despite not being reported, the initial condition and the Mundlak within-means appear positive and significant. Including the within-means takes away the significance of the appropriability and external financial variables. This is partly due to the too little within variation of these variables and that they are highly correlated with their within-means, which poses an identification problem when using the Wooldridge approach.

[17] Disentangling the effect of sunk costs from learning on export persistence in exporting is beyond the scope of this study (see Timoshenko, 2015).

1.5.1.1. *Robustness Analysis*

In this section, we perform some robustness tests based on the models from column (3) in Table 1.4. The results are shown in Table 1.5. For the sake of clarity, we only present the average marginal effects of the ICT and TFP variables[18].

Table 1.5: Robustness checks. Marginal effects of using ICT on export participation for different specifications.

	RE Probit (1)	FE OLS (2)	RE Probit (3)	RE Probit (4)
ICT	0.019***	0.017*	0.010*	0.150***
	(0.005)	(0.010)	(0.005)	(0.037)
TFP	0.026**	0.045**	0.028***	0.022**
	(0.010)	(0.023)	(0.011)	(0.011)
Initial Condition	Yes		Yes	Yes
Mundlak means (all)	Yes			
ICT lagged 2 periods			Yes	
IV Control Function				Yes
Observations	14,932	14,932	13,725	12,508

Notes: The estimates correspond to the average marginal effect of being an ICT user and of TFP in period *t* -1. All specifications include the same controls as in column (1) of Table 1.4, including industry dummies and year dummies. RE and FE mean random effects and fixed effects, respectively. In column (2) a static linear probability FE model is estimated. In column (3) and (4), a dynamic random effect probit model is estimated with the initial condition and the Mundlak means as in column (4) of Table 1.4. In column (4), we use an IV control function approach and, therefore, the regressions include the residual of the first stage estimation of the probability of being an ICT user, which is statistically significant. Block bootstrapped standard errors at firm level in parentheses (500 replications). * Significant at 10%, ** significant at 5%, *** significant at 1%.

In previous specifications, the unobserved firm-specific effect was modeled using only the individual time means of the internal and external financial variables and the appropriability conditions. While this approach helps with the multicollinearity problem, it can cause biases (Semykina, 2018). Then, as a first robustness check, we include all the within-means of the control variables. Looking at the results in column (1), we find that the direct and indirect effect of ICT use is not affected by including all the within-means. ICT use appears to significantly increase the probability of exporting by about 2 percentage points. Moreover, a higher level of TFP is associated with a higher probability of being an exporter, which confirms the indirect effect.

[18] Although all specifications include the same controls as in Table 1.4, for ease of exposition only the results for the variables of interest are presented. Full results are available from the authors on request.

Second, we estimate a linear fixed effects probability model to control for unobserved firm characteristics that are not fully captured by the Wooldridge (2005) approach and that can simultaneously increase the probability of using ICT and exporting. The results in column (2) show that ICT use is positive and significant in determining export status when controlling for firm fixed effects, albeit only at a 10 percent level; while the effect of TFP appears even larger. However, linear probability models have the disadvantage that the estimated probabilities are not restricted to the interval [0–1].

The next robustness checks attempt to solve the problem of potential reverse causality between ICT use and export participation. Although ICT use enters the export equation with a lag, there may still be concerns about potential endogeneity. To address these concerns, we first present in column (3) the results of a random effects dynamic probit model in which the variable for ICT use is lagged by two periods. The direct effect of ICT use remains significant, although the magnitude of the effect decreases (ICT use in *t*-2 increases the probability of exporting in period *t* by one percentage point). As a final robustness check, we use a control function (CF) approach[19] in column (4). The goal is to tackle the endogeneity issue more appropriately by treating it as an omitted variable problem (Wooldridge, 2015). The advantage of this approach is that it can be applied to non-linear models. The CF that we propose to use is the residual of a regression of ICT use on industry and size band investments in hardware and software in *t*-5, plus, the regulatory index in communications drawn from the OECD NMR database[20]. The main identification strategy is that regulations in communication services and early investment in ICT by the industry do not affect the firm's decision to export in period *t*, other than by being correlated with the use of ICT, for instance, due to network effects. Particularly, this method consists of two steps. First, we estimate a reduced-form equation for the probability of being an ICT user based on a Probit model and calculate the generalized residuals[21]. In the second step, we add the residuals to equation (1.1) to filter out the factors that might cause correlation between ICT and the error term. Applying this

[19] For a recent application of the CF approach see García-Vega and Huergo (2019).
[20] The index on the regulatory environment of communications (telecom and post) quantifies information on *ex-ante* anti-competitive restrictions in the market, measured by the extent of entry barriers, the degree of vertical integration and market conduct.
[21] Although for ease of exposition the results of the first-stage probit regression are not shown, the log of investment in the sector and size band in *t*-5, respectively, are positive and statistically significant in explaining firms' ICT use; while the effect of the regulation index is significantly negative.

procedure, we can see that the magnitude of the direct effect of ICT increases. Hence, firms that use ICT are about 15 percentage points more likely to sell in foreign markets. Additionally, the coefficient of the first-stage residual, although not reported, appears statistically significant, which is considered a test for the absence of endogeneity (Rivers and Vuong (1988) endogeneity test). All in all, the results in Table 1.5 show that the use of ICT is a direct facilitator of exports. Moreover, TFP appears positive and significant in all specifications, confirming also the indirect role of ICT in export participation via TFP.

1.5.1.2. Sensitivity Analysis

At this stage, we have shown that ICT has a significant and positive direct effect on the export participation of Spanish manufacturing firms, as well as an indirect effect through the TFP channel. Now, our purpose is to examine which firms and industries benefit most from ICT. Previous studies have shown that the relationship between ICT and firm performance is heterogeneous, with some firms or industries being more successful in exploiting ICT than others (DeStefano *et al.*, 2018).

Thus, we first perform the analysis distinguishing between SMEs and large firms. A priori, it is unclear whether the trade effect of ICT should be larger for smaller or larger firms. On the one hand, small firms might have more to gain from ICT, since it can help mitigate the disadvantages they face in foreign markets (Añón Higón and Driffield, 2011). For example, ICT can enable SMEs that remain in local and regional markets to access foreign customers and expand their markets geographically. With basic ICT applications, such as a website, small firms can rapidly identify and attract new customers in a relatively affordable way, overcoming some of the sunk costs of entering a foreign market. On the other hand, the use of ICT, especially more advanced applications, may require high adjustment costs, e.g., in the form of complementary investment in skills and organizational capital, which may be feasible only for larger firms.

The results presented in Table 1.6 for the variables of interest show that ICT use has a positive and significant direct effect on export propensity only for small and medium-sized firms (see column (1)). That SMEs benefit from the use of ICT applications has been shown in previous studies (Añón Higón and Driffield, 2011; Hagsten and Kotnik, 2017; DeStefano *et al.*, 2018). The use of ICT is a major factor in facilitating the flow of information and expanding the market potential for SMEs by reducing the cost of accessing foreign markets. Our findings suggest that SMEs that use ICT are 2.2 percentage points more likely to export, while this effect is insignificant for large firms (column (2)). Although TFP appears significant for the whole sample, it turns insignificant when we split the sample into large and small firms, albeit positive.

Considering that the take-up of ICT varies widely across industries, we divide the sample into firms that belong to low- and high-digitized industries according to the classification by Calvino *et al.* (2018). In principle, it is also unclear whether the trade effect of ICT is greater for firms in low-digitized industries or vice-versa. While firms in low-digitized industries have more to gain from the adoption of ICT; ICT may be more effective when many firms in an industry use ICT intensively because of knowledge spillovers (Laursen and Meliciani, 2010)[22].

Table 1.6: The effect of ICT-use on the export decision by firm size and sector

	SMEs	Large firms	High digitalization industries	Low digitalization industries
	(1)	(2)	(3)	(4)
ICT	0.022***	0.010	0.013	0.021***
	(0.006)	(0.013)	(0.010)	(0.007)
TFP	0.019	0.015	0.027	0.026**
	(0.014)	(0.030)	(0.021)	(0.012)
Initial condition	Yes	Yes	Yes	Yes
Mundlak means	Yes	Yes	Yes	Yes
Observations	10,857	4,075	5,787	9,145

Notes: The estimates correspond to the average marginal effects of being an ICT user and of TFP in period *t* -1. All columns refer to the same specification as in column (4) of Table 1.4, but with different samples. Block bootstrapped standard errors at firm level in parentheses (500 replications). * Significant at 10%, ** significant at 5%, *** significant at 1%.

The impact of ICT and TFP in industries with low- and high- levels of digitalization is displayed in columns (3) and (4) of Table 1.6, respectively. The results suggest that the use of ICT in low-digitalization industries both directly facilities the entry into foreign markets and has an indirect effect through productivity gains. The direct effect implies that the use of ICT boosts the probability of exporting by 2.1 percentage points. However, the use of ICT does not appear to influence the export decision in high-digitalized industries. In sectors with a high degree of digitalization, the use of ICT is not a distinctive feature that enhances firms' likelihood of exporting. In contrast, it is precisely in more

[22] Laursen and Meliciani (2010) find that domestic and foreign ICT-related knowledge flows exert a positive impact on export shares in ICT industries, while only domestic flows positively affect export intensity in non-ICT industries.

digitally disadvantaged sectors where firms can gain more from the use of ICT, both directly and indirectly through TFP gains.

1.5.2. Intensive Margin Model

The determinants of export intensity are reported in Table 1.7. As explained above, we proceed with a Type II-Tobit model and a generalized two-part fractional model. Results are presented in terms of average marginal effects and their respective block bootstrapped standard errors. Note that we do not include the selection process in the following tables to keep our attention on export intensity, and focus only on the variables capturing the direct and indirect effects of ICT.

Table 1.7: The effect of ICT use on the export intensity margin

	Tobit II-Heckman		Two-part Fractional	
	(1)	(2)	(3)	(4)
ICT	0.004		0.003	
	(0.003)		(0.003)	
Website user		0.004		0.003
		(0.004)		(0.003)
Online transactions		-0.001		-0.001
		(0.003)		(0.002)
TFP	0.019***	0.019***	0.016***	0.016***
	(0.006)	(0.006)	(0.006)	(0.006)
λ (IMR)	0.017	0.017		
	(0.003)	(0.003)		
Initial condition	Yes	Yes	Yes	Yes
Mundlak means	Yes	Yes	Yes	Yes
Observations	14,921	14,921	14,921	14,921

Notes: The estimates correspond to the average marginal effects of being an ICT user and of TFP in period *t* -1 on the export intensity. IMR refers to the inverse Mills ratio. All specifications include the same controls as in column (1) of Table 1.4, including industry dummies and year dummies. All explanatory variables are included with one-period lag. The selection equation and the export-intensity equation contain the terms required to account for initial conditions and for the endogeneity of the lagged dependent variable as in Table 1.4. Block bootstrapped standard errors at firm level in parentheses (500 replications). * Significant at 10%, ** significant at 5%, *** significant at 1%.

First, in columns (1) and (2) we consider the results of the dynamic Tobit II-Heckman model. In both specifications, the *lambda* coefficient of the inverse Mills ratio term is statistically significant ($p < 0.01$), confirming that the export decision is significantly correlated with the export share and thus the appropriateness of the Heckman model. In column (1), we include the ICT user dummy, and in column (2), we separate website users from online transactions. In both columns, ICT appears to be statistically insignificant in explaining export intensity directly, but it still plays a significant indirect role through the productivity channel. All in all, our results suggest that the use of ICT plays a direct role in explaining export participation, but not in explaining the share of foreign sales, for which, however, the indirect TFP channel still plays a significant positive role. Once firms start exporting, the use of ICT allows the share of foreign sales to expand only through TFP gains. We suspect that this is because ICT can increase domestic sales proportionally and therefore the impact on the share of foreign sales is not significant for the average firm.

To ensure the robustness of our results, we also present estimates of a generalized two-part fractional model, which may be more appropriate when the dependent variable is a share (Papke and Wooldridge, 2008). The same variables are used in the Heckman model and the two-part model. Likewise, the results in columns (3) and (4) suggest that the use of ICT does not play a direct role in how much the firm exports, but has an indirect important effect through the productivity channel. This consistency between the models is a sign of the robustness of the results.

1.5.2.1. Sensitivity Analysis

Here, we assess which firms and industries benefit most from ICT. We use the same subsamples as in the sensitivity analysis performed for the extensive margin. We present the results of the Heckman model, given that the above results confirm the correlation between the selection process and the process for positive values, and the results from the two-part model were qualitatively similar. In Table 1.8, we report the marginal effects of using ICT and the effect of TFP[23].

In Table 1.8, the first point to raise is that the Lambda Mills coefficient, although not shown, is significant regardless of the subsample considered, suggesting that the Heckman model is the appropriate model for the aforementioned reasons. Second, TFP is significantly positive in all specifications, regardless of firm size and industry. This implies that ICT plays an indirect role in explaining export intensity through the productivity channel. However, the effect of TFP appears to be larger for large firms and in highly digitized sectors. The use of ICT and export experience lead to productivity gains that increase the firms' share of foreign sales, but to different degrees depending on firm size and sector. Third, after accounting for the indirect effect, results in Table 1.8 suggest that the

[23] For ease of exposition only the results for the variables of interest are presented. Full results are available from the authors on request.

use of ICT is significant only in high-digitized industries, where it has a direct effect of 1.6 percentage points increase on export intensity (column 3). This result reveals that ICT plays a different role in export performance depending on the degree of digitalization of the industries. Hence, the use of ICT in highly digitized industries does not have a direct effect on the export decision but rather on the export intensity, whereas this is the opposite in low-digitized industries. Exporters in highly digitized industries enjoy closer interaction and thus the potential for greater knowledge transfers from global stakeholders, for example, in the form of specialized skills and know-how needed to implement new technologies and knowledge about IT-enabled innovations and practices (Laursen and Meliciani, 2010; Tambe and Hitt, 2014). Thus, exporting firms that use ICT develop absorptive capabilities that enable them to benefit from these global ICT-induced knowledge spillovers. This effect has a larger marginal impact on firms' sales abroad than in their home markets. Thus, the use of ICT contributes both directly and via the TFP channel to enhance firms' international competitiveness in highly digitized sectors.

Table 1.8: The effect of ICT use on export intensity by firm size and sector

	SMEs	Large firms	High digitalization industries	Low digitalization industries
	(1)	(2)	(3)	(4)
ICT	0.004	0.005	0.016***	-0.003
	(0.004)	(0.006)	(0.006)	(0.004)
TFP	0.017*	0.040***	0.031**	0.016**
	(0.009)	(0.011)	(0.013)	(0.008)
Initial condition	Yes	Yes	Yes	Yes
Mundlak means	Yes	Yes	Yes	Yes
Observations	10,855	4,066	5,780	9,141

Notes: The estimates correspond to the average marginal effects of being an ICT user and of TFP in period t -1 on the export intensity. All specifications include the same controls as in column (1) of Table 1.4, including industry dummies and year dummies. All explanatory variables are included with one-period lag. The selection equation and the export-intensity equation contain the terms required to account for initial conditions and for the endogeneity of the lagged dependent variable as in Table 1.4. Block bootstrapped standard errors at firm level in parentheses (500 replications). * Significant at 10%, ** significant at 5%, *** significant at 1%.

1.6. Conclusion

Information and communication technologies are considered to play an important role in facilitating trade because of their potential to reduce transaction costs and improve communication between buyers and sellers, but also owing to their ability to enhance firms' efficiency. A few empirical studies have focused on the direct impact of ICT, particularly the internet, on export activities. In this chapter, as a contribution to the literature, we have analyzed both the direct and indirect effect (via productivity) of ICT on firms' export participation and the intensity of foreign sales. To do so, we use a sample from the ESEE database of Spanish manufacturing firms observed between 2000 and 2014. To unravel the indirect effect, we consider an endogenous Markov process for the dynamics of TFP. Although there are a variety of DTs, we focus specifically on website use and e-commerce. Our findings suggest that firms using ICT experience a direct increase in the probability to export but not in the export intensity. Nevertheless, export intensity increases with ICT due to productivity gains (i.e., the indirect TFP channel).

However, these results vary by firm size and sector. In terms of size, we find that SMEs benefit directly from ICT to participate in foreign markets, and, once they are already in these markets, they benefit indirectly through TFP by increasing their export share. Large firms, on the contrary, benefit only through TFP gains in the intensive margin. Moreover, the use of ICT, and particularly the existence of a website, appears to positively influence the decision whether or not to export for firms in low-digitized industries, it has no direct effect on firms in highly digitized industries. In contrast, ICT in highly digitized industries fosters export intensity both directly and via the TFP channel. It is precisely in a context where DTs are widespread, ICT seems to play a significant role in the export intensive margin, directly due to the existence of ICT-induced knowledge spillovers and indirectly through TFP gains.

The findings presented in this chapter offer important insights for managers, especially in small and medium-sized firms, which have traditionally been characterized by their low participation in overseas markets. By investing in basic DTs, such as a website, SMEs increase their likelihood of exporting. Using a website provides small firms with a platform to advertise their products and share information with potential overseas customers, reducing transaction costs and allowing them to partially offset their disadvantage in foreign markets. Furthermore, the costs associated with leveraging these basic DTs are likely to be lower compared to more traditional network methods or even more advanced DTs. Besides, once the firm is active in international markets, the use of ICT and the firm's previous export experience enhance its productivity, allowing it to become more competitive and increase its share of sales abroad.

As for policy recommendations, the results presented here can help policymakers to better design initiatives to improve the level of competitiveness of Spanish firms, which has been blamed as the major factor behind large and persistent trade deficits. Our results point to a need for policymakers to provide not just the necessary digital infrastructure, but also offer incentives, well in the form of subsidies or tax breaks, to promote the adoption and hence, foster the digital transformation of Spanish firms. This can be especially relevant for SMEs, which face significant financial constraints, or for firms in low-digitized industries; particularly if the aim is to broaden the export base. However, investment in digital infrastructure may not do much if firms lack the digital skills needed to use ICT efficiently. Therefore, training initiatives should be also in place. Even in high-digitized industries, policies aimed at reinforcing firms digital capabilities will have a positive impact on the intensive margin, and thus on firms trade competitiveness.

Our study is not without limitations that open interesting avenues for future research. First, although our findings suggest that the use of ICT does not have a direct effect on the export intensive margin (except for firms in high-digitized industries), this may be due to the way we have measured ICT use. In fact, the results for highly digitized sectors seem to indicate that what matters for the intensive margin is the intensity with which firms use ICT, and not their mere use. High-digitized sectors are those in which DTs are intensively used. To corroborate this, we need information on the extent to which firms use ICT and other DTs, such as cloud-computing. Second, although we have focused on the facilitating role of ICT for exports, DTs can also influence imports. If ICT enable firms to access cheaper and better quality imported intermediates, thereby improving their competitiveness, this could be a new channel through which ICT can contribute to export performance. Future research should therefore include explicitly the outsourcing-enabling mechanism. Other lines of research should contemplate to test the importance of price-cost factors in the model, as in the technology gap tradition, and examine the impact of ICT on the *death of distance*. In this context, data on firms' export destinations could allow us to assess whether ICT can enable trading partners to overcome distance-related effects, both in the physical sense and in the cultural or institutional sense.

Because the effect of ICTs on export participation appears to be particularly relevant for SMEs, we will concentrate solely on this type of firms in Chapter 2. However, rather than considering solely the ICT variables used in this chapter, we broaden our analysis and build a synthetic digitalization index comprehending 13 variables capturing the digital transformation of Spanish manufacturing firms over the last two decades. Moreover, we analyze the impact of this synthetic digitalization index on both export and import participation.

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APPENDIX 1.A

Table 1A.1: Division by industries

Industries	High digitalization	Low digitalization
1. Metals and metal products	-	✓
2. Non-metallic minerals	-	✓
3. Chemical products	-	✓
4. Agric. and ind. machinery	✓	-
5. Electrical goods	✓	-
6. Transport equipment	✓	-
7. Food, drink, and tobacco	-	✓
8. Textile, leather, and shoes	-	✓
9. Timber and furniture	✓	-
10. Paper and printing products	✓	-

Note: "*High digitalization*" identifies sectors classified in terms of digital intensity as High and Medium-high in Calvino *et al.* (2018), while "*Low digitalization*" refers to sectors classified as Low and Medium-low.

Table 1A.2: Description of the variables

Variable	Description
Export propensity	Dummy=1 if the firm exports; =0 otherwise.
Export Intensity	Value of exports/total sales.
ICT use	Dummy=1 if the firm uses has either a website or uses e-commerce; =0 otherwise.
Website user	Dummy=1 if the firm uses a website; =0 otherwise.
Online transactions	Dummy=1 if the firm sells to other firms or final consumers online (B2B, B2C), or purchases online; =0 otherwise.
TFP	The logarithm of the total factor productivity, which is estimated as described in the methodology section.
R&D	Dummy=1 if the firm conducts R&D activities; =0 otherwise.
Human capital	% of employees with a degree.
Age	The logarithm of the age of the firm.
Size	The number of employees.
Foreign capital	Dummy=1 if the firm has foreign capital participation; =0 otherwise.
Appropriability	Dummy=1 if the firm has registered patents either in Spain or abroad, and/or utility models; =0 otherwise.
Recessive market	Dummy= 1 if the firm faces a recessive market demand; =0 otherwise.
Expansive market	Dummy= 1 if the firm faces an expansive market demand; =0 otherwise.
Competitors	Dummy= 1 if the number of competitors reported by the firm is less than 10; =0 otherwise.
External Finance	It reflects the firm's access to internal funds and it is obtained as explained in the Appendix B.
Internal Finance	It reflects the firm's access to external funds and it is obtained as explained in the in the Appendix B.
Output	Sales deflated by a firm-specific output deflator.
Labor	Total effective hours worked.
Intermediate inputs	Value of intermediate consumption (including raw materials, components, energy, and services) deflated by a firm-specific price index of materials.
Non-ICT capital	Following Doraszelski and Jaumandreu (2013), non-ICT capital is measured by the perpetual inventory method with an industry-specific rate of depreciation. Data on investment in technical facilities, machinery and tools, rolling stock and furniture, office equipment, and other tangible fixed assets are used. Real capital is obtained by deflating capital at current replacement values with the price index of investment in equipment goods at the industry level.
ICT capital	This is measured by the perpetual inventory method with a 31.5% depreciation rate (see EU KLEMS) and with data on investment in "equipment for processing information", which includes computers, communication equipment, instruments, and related equipment. To convert nominal values into real ones we use IT capital deflators at the industry level from EU KLEMS.

Table 1A.3: Results of the estimation of the production function

Industry	l	k^{NIT}	k^{IT}	m	Obs.
1. Metals and metal products	0.209***	0.057***	0.009***	0.718***	2,518
	(0.008)	(0.007)	(0.003)	(0.012)	
2. Non-metallic minerals	0.261***	0.032***	0.006	0.721***	1,118
	(0.011)	(0.009)	(0.005)	(0.018)	
3. Chemical products	0.202***	0.037***	0.010***	0.798***	2,040
	(0.008)	(0.009)	(0.003)	(0.021)	
4. Agric. and ind. machinery	0.213***	0.029***	0.010**	0.697***	1,056
	(0.012)	(0.011)	(0.005)	(0.021)	
5. Electrical goods	0.248***	0.014*	0.037***	0.689***	1,148
	(0.011)	(0.008)	(0.004)	(0.020)	
6. Transport equipment	0.204***	0.048***	0.011***	0.743***	1,293
	(0.012)	(0.009)	(0.004)	(0.013)	
7. Food, drink and tobacco	0.114***	0.069***	0.009***	0.708***	2,516
	(0.006)	(0.007)	(0.003)	(0.026)	
8. Textile, leather and shoes	0.316***	0.042**	0.009*	0.384***	1,522
	(0.013)	(0.019)	(0.005)	(0.054)	
9. Timber and furniture	0.222***	0.023***	0.017***	0.631***	1,327
	(0.009)	(0.007)	(0.004)	(0.024)	
10. Paper and printing products	0.248***	0.051***	0.012***	0.608***	1,339
	(0.011)	(0.008)	(0.003)	(0.023)	

Notes: Estimates of the input coefficients from equation (1.4) are shown for different industries using the GMM estimation proposed by Wooldridge (2009). The dependent variable is the log of gross output. Each row represents a separate regression. Robust standard errors are reported in parenthesis. * Significant at 10%, ** significant at 5%, *** significant at 1%.

APPENDIX 1.B

The Internal and External Financial Index

In this study, we use a financial index to proxy both internal and external finance (see Bellone *et al.*, 2010). First, to reflect firms' accessibility to internal funds, we use the cash flow to assets ratio and the profitability ratio, measured by net profit after-sales. We assume that both a higher cash flow ratio and higher profitability imply that firms have lower internal financial constraints. Second, to proxy firm’s accessibility to external funds, we use the cost of new long-term debt (Máñez *et al.*, 2014) and the total volume of new long-term debt. The cost is obtained as a weighted average of the unit cost of debts the firm borrows each year, both from banks and from other long-term lenders. It is believed that the higher interest payment the firms could afford, the lower external financial constraints they are faced with. Moreover, new long-term debt refers to long-term loans obtained from banks and other long-term lenders. Positive values of this variable would correspond to firms that can have access to higher volumes of external debt and, therefore, are less financially constrained. Following Bellone *et al.* (2010), for each variable representing both internal and external finance, we scale each firm/year observation for the corresponding two-digit sector average and then assign to it a number corresponding to the quintiles of the distribution in which it falls. In this regard, sectoral averages are subtracted to account for industry-specific differences in financial variables. The resulting information for each variable (a number ranging from one to five) is then collapsed into two indices, one for internal and other for external finance, using a simple sum.

Chapter 2

2.1. Introduction

It is widely admitted that the digital transformation represents a fundamental potential source of competitiveness and growth for firms in global markets (OECD, 2019). It is in this context that adequate attention needs to be placed so that these new opportunities provided by DTs are not only limited to large enterprises. Since small and medium-sized enterprises (SMEs) play a very significant role in the economy (due to their contribution to the generation of jobs and value-added), it is then desirable that they are stimulated into adopting and integrating new DTs more rapidly and efficiently. Moreover, it has been claimed that the adoption and the smart use of DTs may represent the fundamental basis for their survival[24] (Parker and Castelman, 2007).

In recent years, most developed economies have witnessed an expansion in the involvement of DTs in the process of production and distribution of goods and services (Alcácer *et al.*, 2016). While most studies have focused on the role of digitalization, and more specifically of information and communication technologies (ICTs, henceforth) in the production process (Brynjolfsson *et al.*, 2002; Corrado *et al.*, 2017), its role in distribution, and in particular, in trade has received less attention. Moreover, most of these studies use single indicators of the digitalization phenomenon, which are only able to partially capture the degree of penetration of (certain) DTs and struggle to mirror the fast pace at which the digital transformation has unfolded. Hence, they omit the fact that digitalization is a complex phenomenon that is poorly captured by a single indicator and that different firms and sectors are affected by digital and automated technologies in diverse ways. In this chapter and to overcome these drawbacks, we follow Calvino *et al.* (2018) and construct and synthetic index of digitalization at the firm level that considers the multi-faceted phenomenon of the digital transformation. The ultimate aim of this study is to analyze the relationship between the digital transformation by SMEs in the Spanish

[24] Nevertheless, it has been shown that while large companies have been quick to adopt ICT and other DTs, SMEs have had more serious problems with the requirements and challenges of these new technologies (Swamidass, 2003; Parker and Castelman, 2007).

manufacturing sector and their trade activity. More specifically, we explore how digitalization can facilitate trade in SMEs by focusing on the firms' decisions to both export and import.

The impact of digitalization on trade may be direct or indirect throughout efficiency gains. On the one hand, the digital transformation may enhance trade flows by lowering trade costs and barriers associated with the use of DTs (Yushkova, 2014). In this regard, there are various mechanisms through which DTs may lead to the reduction of trade costs. First, digitalization improves the transparency on the markets, which is an essential condition for exchange, and thus lowers the costs of searching, matching, and communicating with different stakeholders across borders (Hagsten, 2015). Second, DTs provide additional channels for commercial relationships, marketing, and sales, allowing firms to reach larger numbers of digitally connected customers globally. On the other hand, DTs enable firms to source their inputs and organize production more efficiently, thereby enhancing productivity (Fernandes *et al.*, 2019). Furthermore, advances in digitalization can be exploited to facilitate the outsourcing of non-core activities and to support the integration into the global value chain. These potential benefits from the digital transformation may be even greater for SMEs since it can contribute to reduce the internationalization costs related to their size and the difficulty to commit financial and human resources (Cassetta *et al.*, 2020; Hagsten and Kotnik, 2017).

Informed by the results of Chapter 1 and according to the arguments above, we contend that there is a positive relationship between firms' degree of digitalization and the internationalization of SMEs. Certainly, as DTs reduce the costs and the barriers to international trade, such as allowing buyers to easily compare the prices set by different suppliers, we claim that a higher level of digitalization may induce SMEs to export and/or import. Furthermore, digitalization may also indirectly affect trade due to its potential enhancing effect on the firm's productivity (Cardona *et al.*, 2013). In this regard, this study aims to gain additional insights into the relationship between digitalization and export and import activities by distinguishing between a direct effect of the digital transformation on trade activities and, on the other hand, an indirect effect through enhanced productivity. In doing so, data from the *Spanish Survey on Business Strategies* (ESEE) for a sample of Spanish manufacturing SMEs from 2001 to 2014 will be used. A distinguishing feature of the database is that it provides information about the firm's export and import activities, as well as for distinct facets of the digital transformation.

Empirical evidence on the role of DTs on trade using micro-level data is scarce, with few exceptions (see Añón Higón and Bonvin, 2022; Añón Higón and Driffield, 2011; Fernandes *et al.*, 2019; Hagsten and Kotnik, 2017; Kneller and Timmis, 2016). In this chapter, we contribute to previous literature in several ways. First, in contrast to previous studies, we construct a multi-faceted index of digitalization at the firm level. Second, in addition to the direct effect of digitalization on trade performance, we also analyze the effect of digitalization through enhanced productivity. We do so, by estimating in a first stage a production function in which we endogenize the digitalization index and the trade decision and retrieve the firm's total factor productivity (henceforth, TFP). In a second stage, we study the effect of both digitalization and the estimated TFP on the export and import participation decisions. A positive estimate of the TFP variable in the trade participation equations should be considered as evidence of a positive indirect effect of digitalization through enhanced productivity on exports and/or imports. Third, instead of using a static model, we model foreign market participation as a dynamic process[25]. In this respect, our empirical analysis builds on recent literature (Añón Higón and Bonvin, 2022; Brancati *et al.*, 2018; Mañez *et al.*, 2014) and tackles the issues related to the endogeneity of the lagged dependent variable and to the initial conditions problem. Besides, we estimate exports and imports equations jointly in order to account for the fact that they are simultaneously determined (Aristei *et al.*, 2013; Elliott *et al.*, 2019; Exposito and Sanchis-Llopis, 2020). Therefore, we account for the contemporaneous correlation between the two internationalization choices. All in all, our results suggest that digitalization has a significant direct and indirect role in the decision to export and import. The direct effect of digitalization seems to be grater for exports than for imports, while the opposite seems true for the indirect effect.

The remainder of the chapter is organized as follows. The next section reviews the extant literature. We then go on to describe the data and methodological approach, followed by the empirical results. Lastly, we discuss the findings, implications, and limitations of this study.

[25] Although the model of Hagsten and Kotnik (2017) is dynamic in its specification, they estimate the export participation equation using a pooled probit.

2.2. Literature Review

2.2.1. The Link Between Digital Technologies and Trade

In this section, we review existing literature on the relationship between DTs and trade for SMEs. Although recent empirical studies have brought new evidence regarding the positive role of digitalization, and more specifically ICT and the internet, for export performance (see, for instance, Añón Higón and Bonvin, 2022; Fernandes *et al.*, 2019; Kneller and Timmis, 2016), studies focusing specifically on SMEs are scarce. However, because of their limited resources (Bennett, 1997) which impede their ability to compete (Coviello and Martin, 1999), SMEs may benefit from digitalization in a different way than their larger counterparts. Indeed, entering foreign markets has a high sunk cost, which is expected to be more burdensome for smaller firms and could prevent them from internationalization (Melitz, 2003). The internet, for instance, has been proved to reduce trade barriers for SMEs (Hamill and Gregory, 1997) in being a low-cost medium of internationalization (Kim, 2020) and thus, helping them to overcome distance and entry-related costs (Hagsten and Kotnik, 2017), as well as communication costs (Aspelund and Moen, 2004). According to Mata *et al.* (1995), using ICT could provide firms with a competitive advantage, which is one of the reasons that SMEs adopt these technologies at first (Dholakia and Kshetri, 2004).

Although a large number of studies base their findings on country-level data[26], micro studies with firm-level data are relatively rarer. Despite this, micro studies can be classified into two types: studies that focus on firms of all sizes and others that focus solely on SMEs. Among the former, Kneller and Timmis (2016), using data from UK firms between 2000 and 2005, show that broadband use has a positive causal effect on the probability of exporting business services. Similarly, using data of Chinese firms from 1999 to 2007, Fernandes *et al.* (2019) find a causal and significant impact of the internet deployment on manufacturing exports. Moreover, they show that this took place even before the rise of e-commerce platforms. Finally, in Chapter 1, we found that Spanish manufacturing firms using ICTs,

[26] Part of the literature in this field of research uses country-level data and focuses on the macro aspect of the relation between ICT and trade (see for instance, Clarke and Wallsten, 2006; Demirkan *et al.*, 2009; Freund and Weinhold, 2002, 2004a; Yushkova, 2014). The macro literature suggests that there is a positive and significant influence of using ICT on trade.

and in particular those that have a website, experience a direct increase in their probability of exporting, but not in their export intensity (see Añón Higón and Bonvin, 2022). Nevertheless, ICTs increase export intensity indirectly via the productivity channel. Results are particularly interesting when focusing only on SMEs. ICTs appear to have a positive and significant direct effect on the probability to export, whereas this effect is non-existent when looking at large firms.

Other studies have put the focus on SMEs. For instance, Loane (2005), using a sample of SMEs from Ireland, Canada, New Zealand, and Australia, finds that the internet enables SMEs to trade globally even at an early stage of development. Hagsten and Kotnik (2017) show that, for a sample of SMEs from 12 European countries, basic ICT tools, such as having a website, are more important for entering foreign markets than advanced ICT tools, such as e-commerce, which play a more crucial role in export intensity. The UK has received ample evidence. Within the early studies, Hamill and Gregory (1997) suggest that the internet is well suited to help SMEs to overcome trade-related barriers, and this even when the Internet was at a very early stage of development. More recently, Mostafa *et al.* (2005) using 5 ICT indicators (resources committed to the internet, internet usage, perceived benefits, web function, and internet experience) find that the Internet helps to improve trade, especially when firm managers have a strong entrepreneurial orientation, which would make them more likely to benefit from the opportunities offered by the Internet. Similarly, Añón Higón and Driffield (2011) identify a positive correlation between the use of ICT by firms and the propensity to export, as well as the export intensity. Morgan-Thomas and Jones (2009) find a strong association between internet use and rapid business internationalization, while Sinkovics *et al.* (2013) argue that the Internet, if used as a sales channel, should be complemented with other tools, such as advertising or delivery support, in order to increase export performance. Using respectively a sample of UK and Norwegian SMEs, Tseng and Johnsen (2011) and Aspelund and Moen (2004) evidence that the Internet has a greater impact on high-tech SMEs than on their low-tech counterparts. More recently, Jin and Hurd (2018) illustrate that digital platforms, Alibaba in particular, help SMEs to overcome some entry barriers into foreign markets, while Lendle *et al.* (2012) find a similar result for eBay. Finally, as far as Spanish firms are concerned, using the Survey of Business Strategies, Nieto and Fernandez (2005) evidence that there is a positive effect on SMEs' export intensity of selling to other businesses online, while selling to final consumers or having a website do not have a significant effect. Hence, there seems to be a consensus that using DTs, and more specifically, internet-related technologies, has a positive effect on the export performance of SMEs and therefore, on their internationalization process.

However, most of the above literature focuses on exports and overlooks the importance of digitalization for imports. Certainly, imports can also be facilitated by more extensive use of DTs, as the cost of imports can be reduced through lower communication and coordination costs (Jungmittag and Welfens, 2009). Hence, thanks to digitalization, information can circulate more rapidly, allowing buyers and sellers to find each other at lower costs. This is, at least partly, responsible for what we commonly refer to as the death of distance, for both imports and exports (see Freund and Weinhold, 2004b; Demirkan *et al.*, 2009). In this regard, DTs are replacing face-to-face interactions with, for instance, interactions by phone or email (Dettmer, 2014).

Few studies analyze the impact of digitalization on imports. Using a panel of 49 countries between 2000 and 2013, Nath and Liu (2017) provide evidence that the development of ICT facilitates imports of financial services, insurance services, other business services, royalty and license fees, and telecommunication services. Similarly, Ozcan (2018), for a sample of countries trading with Turkey between 2000 and 2014, shows a positive effect of ICT development on both exports and imports volumes, the effect being larger for imports. More lately, and at a micro-level, a couple of studies have shifted the focus away from ICT and analyzed the role of the adoption of automated technologies, mainly robots, on imports. For example, Stapleton and Webb (2020) find a positive effect of robot adoption by Spanish firms on their imports from low-income countries over the period 1990 to 2016. This effect is mainly caused by firms starting to import from low-income countries as a result of automation. However, the effect of adopting robots for firms that were already importing from low-income countries before robot adoption is to shift some of their imports away from low-income countries towards high-income countries. The conclusions of Alguacil-Marí *et al.* (2022) are quite similar. Using a sample of Spanish manufacturing firms between 1994 and 2014, they show that the adoption of robots helps firms to start importing and exporting, and increases the value and weight of imports in total sales. Likewise, they also evidence an eventual shift from low labor costs countries to higher labor costs countries, ensuring greater quality and technology of inputs. Overall, these studies suggest that digitalization and automation have a positive effect on imports. Nevertheless, these studies do not take into account that the decision to export and import are determined simultaneously (Elliott *et al.*, 2019; Exposito and Sanchis-Llopis, 2020).

2.2.2. The Link Between Digital Technologies and Productivity

Knowing the cost-reducing nature of digitalization, we also expect it to have a productivity-enhancing effect. Hence, we argue that digitalization affects trade directly, but indirectly too through the enhancement of productivity. The analysis of the indirect impact of digitalization on exports and imports through productivity gains thus relates this study to a constantly expanding literature on the role of digital and automated technologies on firm productivity. The arguments by which DTs are said to have strong positive effects on productivity are diverse (Syverson, 2011). Digitalization endows firms to source their inputs and organize production more efficiently, and it facilitates changes in management and organization practices (Arvanitis and Loukis, 2009; Bloom *et al.*, 2014). Hence, it is argued that ICT, and other digital and automated technologies, are key enablers of innovation and technical change, and thus, foster productivity gains (Brynjolfsson and Saunders, 2009; Jovanovic and Rousseau, 2005). Yet, the empirical evidence, particularly at the firm level, is rather mixed.

When it comes to the empirical evidence, early studies found limited evidence of the positive impact of ICT on productivity (for an overview, see Cardona *et al.*, 2013). For instance, Loveman (1994) finds no evidence of IT having a significant effect on productivity based on firm-level data from the US and Western Europe between 1978 and 1984. Berndt and Morrison (1995) and Brynjolfsson (1996), both using data from the US between 1968 and 1986, and 1987 and 1991 respectively, reach similar conclusions and show no significant effect of ICT on productivity.

In turn, as technology diffused and adoption rates increased, the number of firm-level studies finding a positive significant effect on productivity increased. Brynjolfsson and Hitt (2003), using data from 527 US firms from 1987 to 1994, show that computerization has a positive impact on productivity in the long term but not in the short term. O'Mahony and Vecchi (2003) also conclude a long-term impact of ICT on TFP using industry panel data from the US and UK between 1976 and 2000. Hempell (2005), with firm-level data from Germany over the 1994-1999 period, evidences a positive impact of ICT on the productivity of firms in the service sector. Commander *et al.* (2011), using firm-level data from manufacturing firms in Brazil and India, also find a strong and positive association between ICT capital and productivity.

More recently, the productivity slowdown has sparked renewed interest in the role of DTs, albeit again with mixed results. Using US firm-level data from 1977 to 2007, Acemoglu *et al.* (2014) find that the intensity of IT has no effect on manufacturing productivity, except in the computer-producing industry. According to DeStefano *et al.* (2018), broadband has a causal effect on firm size but not on productivity in UK establishments in the early 2000s. In contrast, Bartelsman *et al.* (2019) find a positive relationship between the share of broadband-connected employees and productivity for a sample of European firms from 2002 to 2010. Similarly, Gal *et al.* (2019) show a strong relationship between the adoption of DTs in a sector and productivity gains at the firm level for a large sample of OECD firms.

In contrast to extant literature and in line with Chapter 1, we propose that digitalization endogenously affects TFP. By opting for an endogenous process in the dynamics of TFP, as proposed by Doraszelski and Jaumandreu (2013) for R&D, we account for uncertainties linked to the success of the digitalization process, which might explain the heterogeneous results obtained in previous studies. Further contributions to the literature discussed above are made. First, we use a multi-dimensional digitalization index, which includes 13 dimensions of the digital transformation along the lines of the taxonomy presented in Calvino *et al.* (2018). This allows us to better capture the degree of digitalization than including separate dummies that only consider, for example, the use of the internet or the presence of e-commerce. We also differ from previous studies in that we consider both the direct and indirect effect, through TFP, of digitalization on trade. In addition, we also examine the interdependent relationship between imports and exports. To do so, we estimate the decision to export and import simultaneously within a dynamic random-effects model based on recent literature (Brancati *et al.*, 2018; Elliot *et al.*, 2019) and attempt to control for the potential endogeneity of digitalization.

2.3. Methodology

To analyze the role of the digital transformation as a trade facilitator for SMEs, we estimate a model that considers the impact of digitalization on the *extensive margin* of both exporting and importing, i.e., the propensity to export (import) or the probability to participate in foreign markets though export (import). More specifically, this model is based on the model proposed by Roberts and Tybout (1997). According to this model, firms decide to export (import) when current and expected revenues exceed current costs and any sunk cost the firm faces in accessing foreign markets. Therefore, to model the SMEs propensity to export (import), we assume that firm *i* decides to export (import) in period *t* if the expected present value of profits from exporting (importing), EXP_{it}^{*} (IMP_{it}^{*}), is positive. Formally,

$$\begin{cases} EXP_{it}^{*} = \alpha_i^{exp} + \delta^1 DIG_{it} + \gamma^1 TFP_{it-1} + \beta^1 X_{it-1} + \eta^1 EXP_{it-1} + \theta^1 IMP_{it-1} + d_j + d_t + \varepsilon_{it}^1 \\ IMP_{it}^{*} = \alpha_i^{imp} + \delta^2 DIG_{it} + \gamma^2 TFP_{it-1} + \beta^2 X_{it-1} + \eta^2 IMP_{it-1} + \theta^2 EXP_{it-1} + d_j + d_t + \varepsilon_{it}^2 \end{cases} \tag{2.1}$$

where EXP_{it}^{*} (IMP_{it}^{*}) is a latent variable that represents the unobserved profitability of engaging in exports (imports), which in turn depends on the firm's digital transformation (DIG_{it}), the lagged TFP (in logs), which controls for the indirect effect of digitalization on export (import) via the productivity channel (TFP_{it-1}), and a vector of other lagged observable explanatory variables represented by X_{it-1}. Moreover, both α_i represent the time-constant unobserved firm-specific effect, while d_j denotes industry fixed effects at the two-digit level, and d_t is a set of time effects. Finally, EXP_{it-1} and IMP_{it-1} are dummies accounting for previous (realized) export (import) experience, and are included to capture sunk-entry costs. The effect of other time- and firm-specific unobservable determinants are summarized in the idiosyncratic error terms, ε_{it}.

However, instead of observing the latent variable, EXP_{it}^{*} (IMP_{it}^{*}), we only observe a binary variable, EXP_{it} (IMP_{it}), which indicates the sign of the latent variable and states whether firm *i* engages in exporting (importing) in year *t* or not. Hence, the observed binary variable and its underlying latent counterpart are related according to:

$$EXP_{it} = \begin{cases} 1, & EXP_{it}^{*} \geq 0 \\ 0, & EXP_{it}^{*} < 0 \end{cases} \tag{2.2}$$

$$IMP_{it} = \begin{cases} 1, & IMP_{it}^{*} \geq 0 \\ 0, & IMP_{it}^{*} < 0 \end{cases} \tag{2.3}$$

It is also important to emphasize that η in equation (2.1) is the parameter of persistence of the dependent variable induced by the existence of sunk costs. If η is positive and significant, it implies that SMEs that export (import) in *t*-1 are more likely to export (import) in *t* than if they do not export (import) in *t-1*. However, to estimate η consistently, it is necessary to account for both unobserved heterogeneity[27] and the initial conditions problem. Indeed, the first observation of EXP_{it} (IMP_{it}) is correlated with both the unobserved heterogeneity term α_i (Heckman, 1981) and all the future realizations of EXP_{it} (IMP_{it}). This entails that EXP_{it-1} (IMP_{it-1}) is correlated with the unobserved firm-specific time-invariant effects, α_i, and this will yield inconsistent estimates, unless the initial condition is accounted for. To address this issue, we follow Wooldridge (2005) who suggests making assumptions about the distribution of the unobserved effects conditional on observed covariates and adopting a conditional maximum likelihood approach (Chamberlain, 1982; Semykina, 2018). Therefore, we assume that the unobserved firm-specific term in the export equation can be modeled as follows:

$$\alpha_i^{exp} = \delta_1^{exp}\overline{q_i} + \delta_2^{exp}EXP_{i0} + u_i^{exp} \tag{2.4}$$

Or in the case of importing:

$$\alpha_i^{imp} = \delta_1^{imp}\overline{q_i} + \delta_2^{imp}IMP_{i0} + u_i^{imp} \tag{2.5}$$

where $\overline{q_i}$ is a vector including the Mundlak-Chamberlain means (Chamberlain, 1982; Mundlak, 1978). In other words, it represents the within-means of the control variables that are likely to be correlated with α_i. In this regard, we follow Semykina (2018) and assume in the baseline specification that the

[27] To control for unobserved firm heterogeneity, both fixed-effects and random-effect specification can be used. However, since the model is nonlinear, the standard fixed effect panel method would produce inconsistent estimators (Semykina, 2018).

unobserved individual effects are only correlated with the firm's internal and external financial constraints[28]. In the present context, the time means can be interpreted as measures of the firm's financial stability, which can also be viewed as proxies for unobserved firm-specific characteristics (e.g., management quality). As a robustness check, we also consider a specification that includes the within-means of all exogenous variables included in X. On the other hand, EXP_{i0} (IMP_{i0}) represents the initial conditions, and both u_i's are the unobserved time-invariant heterogeneity terms, which are assumed to be independent of the initial conditions, the explanatory variables, and the respective idiosyncratic error term (ε_{it}).

Finally, we substitute equations (2.4) and (2.5) into (2.1) to obtain the final model:

$$\begin{cases} EXP_{it}^{*} = \delta^1 DIG_{it} + \gamma^1 TFP_{it-1} + \beta^1 X_{it-1} + \eta^1 EXP_{it-1} + \theta^1 IMP_{it-1} + d_j^{exp} + d_t^{exp} \\ \qquad + \delta_1^{exp}\overline{q_\iota} + \delta_2^{exp} EXP_{i0} + u_i^{exp} + \varepsilon_{it}^1 \\ IMP_{it}^{*} = \delta^2 DIG_{it} + \gamma^2 TFP_{it-1} + \beta^2 X_{it-1} + \eta^2 IMP_{it-1} + \theta^2 EXP_{it-1} + d_j^{imp} + d_t^{imp} \\ \qquad + \delta_1^{imp}\overline{q_\iota} + \delta_2^{imp} IMP_{i0} + u_i^{imp} + \varepsilon_{it}^2 \end{cases} \tag{2.6}$$

Although the two equations displayed above look like seemingly unrelated regression equations, it is important to note that they are in fact correlated via the error terms, as the lagged dependent variable in the first equation is part of the explanatory variables in the second, and vice versa (Elliott *et al.*, 2019; Exposito and Sanchis-Llopis, 2020). The Conditional Mixed Process (CMP) framework implemented by Roodman (2011) allows us to combine both equations and estimate them jointly. Thus, ε_{it}^1 and ε_{it}^2 are the error terms of each equation with $\rho = Corr(\varepsilon_{it}^1, \varepsilon_{it}^2)$. If ρ is significantly different from zero, then EXP_{it}^* and IMP_{it}^* are two interdependent processes, and a joint estimation is more efficient than estimating two separate probit models.

2.3.1. Modeling the Indirect Effect of Digitalization Through TFP

To analyze the indirect effect that digitalization may play on the trade strategies of SMEs, we need first to estimate TFP. Thus, to see whether digitalization enhances firms' productivity, we estimate a

[28] The approach used by Semykina (2018) differs from the Wooldridge (2005) approach in that, instead of using the within means of all time varying variables in X, it takes only the time means of a subset of variables (q) that are theoretically more likely to be correlated with the unobserved individual effects (α_i).

production function that considers the possible effect of digitalization on the productivity process. Thus, firm-level TFP is estimated for SMEs in each two-digit industry from the following Cobb-Douglas production function:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + \omega_{it} + e_{it} \tag{2.7}$$

where we denote the logarithm of real gross output, labor, non-ICT physical capital, ICT capital, and materials as y_{it}, l_{it}, $k_{it}^{NIT}, k_{it}^{IT}$, and m_{it}, respectively. In addition, ω_{it} is the firm's productivity, and e_{it} is the error term. Labor and materials are assumed to be freely variable inputs, while both types of capital are regarded as fixed factors.

A crucial assumption in the estimation is the specification of the Markov process for productivity, in which productivity at time $t+1$ consists of expected productivity given a firm's information set, and an innovation term, ξ_{it+1}, which is assumed uncorrelated with the state variables. Following Doraszelski and Jaumandreu (2013) and De Loecker (2013), we propose an endogenous (first-order) Markov process, in which we allow the digitalization index (DIG) and the trade status[29] (*XM*) to impact future productivity:

$$\omega_{it+1} = g(\omega_{it}, DIG_{it}, \ XM_{it}) + \xi_{it+1} \tag{2.8}$$

where g(.) is an unknown function. By using an endogenous productivity process, we control for potential learning effects. In this way, we account for the potential role that both firm's experience in digitalization and trade may play in shaping future productivity.

The discussion now turns to the estimation process. The estimation of equation (2.7) by OLS will result in biased and inconsistent estimates because the firm's choice of inputs, especially variable inputs, depends on the firm's productivity, ω_{it} (which is assumed to be observed by the firm but not by the analyst). To address this endogeneity problem and consistently estimate the parameters in (2.7), we

[29] Trade status (*XM*) is a dummy that takes the value of one if the firm exports or imports, and zero otherwise.

use the control function approach pioneered by Olley and Pakes (1996). More specifically, we apply the GMM estimation proposed by Wooldridge (2009)[30]. In doing so, we assume that the demand for intermediate inputs is a function of firms' ICT and non-ICT capital, as well as productivity. Moreover, such demand for intermediates is monotonic and strictly increasing in productivity, and, under certain conditions, it can be inverted to obtain: $\omega_{it} = m_t^{-1}(k_{it}^{IT}, k_{it}^{NIT}, m_{it}) = h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it})$. Then, substituting into (2.7) we get the first equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it}) + e_{it} \tag{2.9}$$

Since h_t (.) is an unknown function, which we proxy by a third-degree polynomial in its arguments, this results in the coefficients of capital and materials being non-identified in (2.9). Hence, the identification of these coefficients requires an additional equation (Wooldridge, 2009). This equation is the first-order endogenous Markov process described by (2.8).

Considering that $\omega_{it} = h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it})$, equation (2.8) can be rewritten as $\omega_{it} = f(h_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}), DIG_{it-1}, XM_{it-1}) + \xi_{it} = g_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DIG_{it-1}, XM_{it-1}) + \xi_{it}$; and plugging this expression into (2.7) we obtain the second equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + g_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DIG_{it-1}, XM_{it-1}) + u_{it} \tag{2.10}$$

where g_t (.) is an unknown function proxied by a third-degree polynomial in its arguments, and where $u_{it} = \xi_{it} + e_{it}$ is a composed error term.

Following Wooldridge (2009), equations (2.9) and (2.10) are jointly estimated by GMM using the appropriate instruments[31] for each of the 10 industries considered. As a result, we obtain industry-

[30] The method distinguishes between state variables, in our case both types of capital, and flexible variables, here labor and materials. The realization of the state variables in period *t* is decided based on the information in *t*-1, and thus they are not affected by the productivity shock arriving *t*, while flexible variables are determined in response to the shock.
[31] We follow Doraszelski and Jaumandreu (2013) and De Loecker (2013) and do not account for sample selection by modelling a firm's exit decision.

specific output elasticity estimates as well as firm-specific TFP estimates obtained as residuals. Table 2.1 reports the estimates of the production function (2.7) for each industry considered for the sample of SMEs. The results show that the output elasticity of ICT-capital is significant for all industries, except for the transport equipment industry, and it ranges from 0.006 in the metals and metal products industry to 0.045 in the electrical goods sector. Output elasticities of non-ICT capital, labor and intermediate inputs display positive and significant across all industries considered in the analysis and with the expected size.

Once the estimated TFP is obtained as a residual for each of the two-digit industries, we winsorize the resulting distribution at the 1st and 99th percentiles to control for the impact of outliers. Then, TFP is included as a regressor in the export (import) participation equations. Finally, it should be noticed that for digitalization to have an indirect effect through TFP on export (import) performance, two conditions should be met. First, the digitalization index should have a significant effect on productivity; and, second, the coefficient of TFP in the export (import) participation equation should be positive and significant. Then, a positive and significant estimate for the TFP variable in the export (import) propensity equation should be considered as evidence of a positive indirect effect accruing from firms' digital transformation to export (import) participation through enhanced productivity.

To check the first condition, we will consider a linear specification of the endogenous Markov process described by equation (2.8):

$$\omega_{it} = \beta_1 \omega_{it-1} + \beta_2 DIG_{it-1} + \beta_2 XM_{it-1} + \gamma' z_{it-1} + \alpha_{jt} + \alpha_i + \epsilon_{it} \qquad (2.11)$$

where TFP (ω_{it}) is a function of its lag value (ω_{it-1}), the *digitalization* index (DIG_{it-1}), and the trade status (XM_{it-1}). In addition, we control for other factors that may influence the evolution of productivity including a vector of observed firm characteristics[32] (z_{it-1}), sector-year dummies (α_{jt}), and firm fixed effects (α_i). We interpret positive and significant estimates of β_2 as evidence of enhancing TFP effects from digitalization. Equation (2.11) is estimated by the two-step system-GMM estimator for dynamic

[32] We control also for firm's size, age and foreign ownership.

models (Arellano and Bover, 1995; Blundell and Bond, 1998), which deals with both unobserved heterogeneity and the endogeneity bias.

Table 2.1: Results of the estimation of the production function for SMEs

Industry	***l***	k^{NIT}	k^{IT}	***m***	**Obs.**
1. Metals and metal products	0.233***	0.055***	0.006**	0.688***	1,734
	(0.011)	(0.009)	(0.003)	(0.016)	
2. Non-metallic minerals	0.212***	0.045***	0.014***	0.728***	798
	(0.015)	(0.014)	(0.005)	(0.025)	
3. Chemical products	0.237***	0.049***	0.009***	0.717***	1,334
	(0.012)	(0.011)	(0.003)	(0.021)	
4. Agric. And ind. Machinery	0.202***	0.039***	0.023***	0.700***	765
	(0.015)	(0.015)	(0.006)	(0.022)	
5. Electrical goods	0.222***	0.072***	0.045***	0.634***	695
	(0.014)	(0.016)	(0.006)	(0.031)	
6. Transport equipment	0.202***	0.082***	0.005	0.744***	542
	(0.019)	(0.017)	(0.008)	(0.028)	
7. Food, drink and tobacco	0.106***	0.080***	0.014***	0.714***	1,695
	(0.008)	(0.009)	(0.003)	(0.023)	
8. Textile, leather and shoes	0.362***	0.080***	0.012**	0.450***	1,213
	(0.016)	(0.017)	(0.006)	(0.039)	
9. Timber and furniture	0.230***	0.031***	0.019***	0.679***	1,116
	(0.011)	(0.010)	(0.004)	(0.022)	
10. Paper and printing products	0.275***	0.122***	0.010**	0.460***	1,012
	(0.013)	(0.016)	(0.005)	(0.056)	

Notes: Estimates of the input coefficients from equation (2.7) are shown for different industries using the GMM estimation proposed by Wooldridge (2009). The dependent variable is the log of gross output. Each row represents a separate regression. Robust standard errors are reported in parenthesis. *** denotes level of significance at 1%, ** at 5%, * at 10%.

2.3.2. Additional Explanatory Variables.

We include in the vector X_{it-1} of equation (2.6) additional variables that previous literature has considered to influence the decision to engage in trade activities (Brancati *et al.*, 2018; Mañez *et al.*, 2014, 2020). First, we control for the firm's market power, as measured by markups (Máñez *et al.*, 2020), relative to the average markup in the industry. The markup is defined as the ratio of firms' output price (P_{it}) to marginal cost (MC_{it}). While the theory predicts that exporters may charge higher markups than non-exporters due to their productivity premium, if they face tougher competition abroad than at home, they will have to reduce markups to remain competitive there or they may choose to rely on dynamic pricing strategies, charging lower prices to build up a customer base. As a result, the average firm markup, conditional on physical productivity, might be lower for SMEs exporters than for non-exporters. To obtain firms' markups we use the methodology proposed by De Loecker and Warzynski (2012). This methodology does not require any assumptions on the shape of the demand faced by firms or on how firms compete. The only assumptions required are that: i) there is at least one variable factor of production, and, ii) firms are cost minimizers. Hence, from the first order condition of the cost minimization with respect to the variable input, one can compute the firm's markup (μ). Here we use intermediate inputs as the variable factor of production, given that labor in Spain may be subject to more rigidities. Hence, following De Loecker and Warzynski (2012), the estimate of the firm's markup can be obtained as the ratio between the output elasticity of the intermediate inputs (β_m), obtained from the estimation of equation (2.7), and the cost share of intermediate inputs relative to total sales $\left(\frac{P_{it}^m M_{it}}{P_{it} Q_{it}}\right)$ that comes directly from the date. More specifically,

$$\mu_{it} = \frac{\beta_m}{\left(\frac{P_{it}^m M_{it}}{P_{it} Q_{it}}\right)} \tag{2.12}$$

Second, we control for the firm's internal and external finance. Numerous studies have addressed the role that financial factors and liquidity play in internationalization activities, especially in the export decision. All in all, results from the literature using different variables (and approaches) to measure internal and external financial resources show that firms with liquidity constraints have greater difficulty in starting to export (see Wagner, 2014) and are less likely to import intermediate goods (Nucci *et al.*, 2020). In this study, we use a multivariate financial index that captures both internal and external finance, respectively (see Bellone *et al.*, 2010). First, to reflect firms' accessibility to internal funds we use the cash flow-to-assets ratio and the profitability ratio, measured by net profit after sales, as variables for the internal finance index. Both, a higher cash flow ratio and higher profitability may imply that firms have lower internal financial constraints[33]. Second, we use the cost of new long-term debt (Mañez *et al.*, 2014) and the total volume of new long-term debt to measure firms' accessibility to external funds.

[33] While a higher cash flow ratio is usually regarded a sign of financial health, there are studies that suggest that firms may be forced to be liquid because they are unable to access external resources (Almeida *et al.*, 2014).

The cost is obtained as the weighted average of the unit cost of debts that the firm has borrowed in a given year from both banks and other long-term lenders. It is generally assumed that the higher the interest payment the firms can afford, the lower the external financial constraints they face. In addition, new long-term debt refers to long-term loans obtained from banks and other long-term lenders in a given year. Positive values of this variable would correspond to firms that have access to a higher volume of external debt and, therefore face fewer financial constraints.

Following Bellone *et al.* (2010), for each variable representing both internal and external finance, we scale each firm/year observation for the corresponding two-digit sector average and assign to it a number corresponding to the quintiles of the distribution in which it falls. The resulting value for each of the variables (a number between one and five) is then collapsed into two indices, one for internal and one for external finance, using a simple sum.

In addition, we include in the vector of controls the firm's age, R&D propensity, size (measured by the number of employees), human capital, foreign capital participation, appropriability conditions, firm's business cycle (measured by the firm's assessment of whether the demand in its main market is recessive or expansive), and the firm's number of market competitors[34]. To deal with the potential simultaneity bias, these variables enter with one lag in the model specification.

2.3.3. Control Function Approach

As in Chapter 1, we also use a control function (CF) approach. The aim here is to address the potential endogeneity of the digitalization index in the trade equation more appropriately, treating the issue as an omitted variable problem (Wooldridge, 2015). This approach has been shown to produce more consistent estimates than two-stage least squares for non-linear models (Wooldridge, 2015). The CF operates by first estimating DIG_{it} – our potentially endogenous variable of interest – as a function of the instruments and other exogenous variables, and then inserting the predicted residuals from this first stage into equation (2.6) as a separate control variable[35]. The instruments that we first propose are the second lag of the digitalization index and the industry regulatory index in communications drawn from the

[34] Table 2A.1 in the Appendix presents the definition of variables.

[35] This residual is, by definition, uncorrelated with the endogenous variable and provides an unbiased CF estimator that is generally more precise than the IV estimator (Wooldridge, 2010).

OECD NMR database, already used in Chapter 1. It is common to use lagged variable as instruments in the literature (e.g., Cameron *et al.*, 2005). The standard argument is that previous values have already been set and should not be correlated with the current errors. We also expect that regulation in communication services to be negatively correlated with the diffusion of DTs among firms. However, we argue that both the regulation index and the second lag of the digitalization index do not affect the firm's trade participation decisions in period *t*, other than by being correlated with the digitalization index in period *t*. Thus, in the first step, we estimate a reduced form equation for the digitalization index based on a fixed effect model and calculate the residuals of this equation. In this regression, the instruments must be significant to be valid. In the second step, the residual is added to both equations in (2.6) to filter out the factors that might cause correlation between the digitalization index and the error term (Newey, 1987; Blundell and Powell, 2004). The statistical significance of the residual in the second stage allows checking for the existence of an endogeneity problem for the digitalization index (Rivers-Vuong endogeneity test). If this is the case, the inclusion of the residual would correct for the bias. Note that we also use the CMP approach in this specification and estimate both equations jointly.

2.4. Data and Descriptive Statistics

2.4.1. Data

The data used in this study have been drawn from the Survey on Business Strategies (ESEE, henceforth) for the period 2001-2014. The ESSE is an annual panel database, carried out since 1990, sponsored by the Spanish Ministry of Industry, Tourism and Trade and, administered by the SEPI Foundation. The ESEE is representative of Spanish manufacturing firms classified by two-digit manufacturing industries of the NACE-Rev.1 and size categories. In particular, the ESEE provides information about firms' strategies, i.e., decisions firms take regarding their competition. The questionnaire covers information on: the firm's activity, products and manufacturing processes, customers and suppliers, costs and prices, markets, technological activities, foreign trade; and, accounting data. Yet, some of the questions relative to the digital transformation, in particular online trade and training in ICT appear since 2000 and 2001, respectively, which is why our period of analysis starts in 2001.

The sampling procedure of the ESEE is as follows. Firms with less than 10 employees were initially excluded from the survey. Firms employing between 10 and 200 workers were randomly sampled, holding about 5% of the population in 1990. All firms with more than 200 employees were surveyed on a census basis, obtaining a participation rate of around 70% in 1990. Important efforts have been made to minimize attrition and to annually incorporate new firms with the same sampling criteria as in the base year. Hence, the sample of firms remains representative over time.

Our initial sample consists of an unbalanced panel of about 25,056 observations corresponding to firms observed at least two consecutive periods from 2001 to 2014. From this initial sample, to analyze the impact of the digital transformation on the export and import strategies of SMEs, we sample out large firms and those firms that fail to supply relevant information in any given year. After cleansing the data, we end up with a sample of 12,783 observations corresponding to 1,814 small and medium-sized firms.

Regarding our variables of interest, the ESEE provides information about whether the firm exports (imports). For the firm's export status, we use the following question: "*Indicate whether the firm, either directly or through other firms from the same group, has exported during this year (including exports to the European Union)*". Similarly, for the import status, we use the question: "*Indicate whether the firm, either directly or through other firms from the same group, has imported during this year (including imports from the European Union)*".

2.4.2. The Digitalization Index

The key indicator of digitalization at the firm level used in this study is based on the work of Calvino *et al.* (2018), adapted according to the availability of data in the ESEE. This index is conceived under the consideration that the digital transformation is a complex phenomenon that can hardly be captured by a single indicator, and that firms and sectors are affected by DTs in a heterogeneous way. Moreover, DTs are interrelated, with the impact of one technology being enhanced by the use of another technology (Bartelsman *et al.*, 2017). Hence, the effectiveness of DTs should be assessed considering them as a whole and not individually.

To create this index, we use several dimensions of the digital transformation that aim to represent the extent of digitalization of firms in Spain[36]. These dimensions are: i) the technological components (proxied by ICT capital, computer programming services, and the implementation of software programs either hired or developed by the focal firm); ii) the digital-related human capital (proxied by personnel training in software and information technology); iii) the extent of automation (proxied by the use of robots, computer-aided design, flexible systems, and the use of LAN); iv) the way digitalization changes how firms interact with their stakeholders (measured by the ownership of an internet domain and webpage, and the use of different modalities of e-commerce: b2b, b2c, and e-buying). In total, the synthetic index collapses information on 13 variables that measured in different ways contain relevant information relative to the digital transformation. In Table 2B.1 of Appendix 2.B, we compare the dimensions and variables we use to those of Calvino *et al.* (2018). We will also analyze distinctively the role of automation from other DTs, which we will refer as ICTs. Hence, the automation index will capture the use of robots, computer-aided design, flexible systems, and LAN, or in other words the automation component in the digitalization index of Calvino *et al.* (2018).

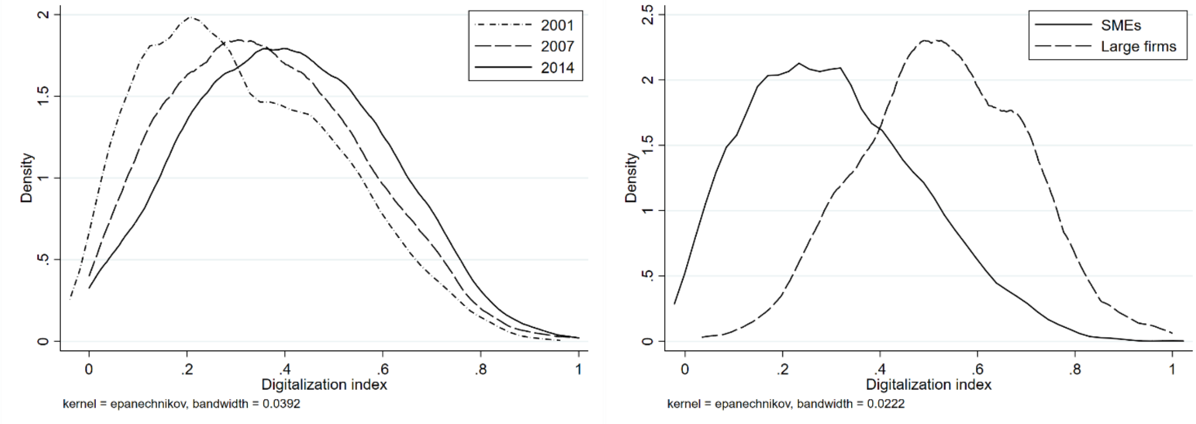
The procedure to build the overall digitalization index can be summarized as follows. First, variables in monetary units (ICT investment and training costs) are capitalized and their relative value with respect to the industry-year mean is classified according to the decile of the distribution to which they belong. The result is then rescaled in the [0-1] range. Categorical variables available only every 4 years (use of robots, CAD, flexible systems and LAN), are first extrapolated and then normalized in the [0-1] interval. The rest of the categorical variables are not transformed. As a result, we end up with 13 variables ranging from 0 to 1. Finally, to obtain a synthetic index, we combine the information of these variables as an unweighted sum. The result is subsequently normalized in the [0-1] interval. Values close to 0 imply that the firm in that period is very little digitalized, while values close to 1 suggest a high degree of digitalization in the dimensions considered.

In Figure 2.1, we show the digital transformation of manufacturing firms in Spain over the period 2001 to 2014 using the synthetic digitalization index as described above. According to the left

[36]For a detailed explanation of the index and its components refer to Appendix 2B.

panel of Figure 2.1, we observe that firms in Spain have undergone a process of digital transformation, which was much faster at the beginning of the 21 century and that slowdown later on as a result of the 2008 financial crisis. Moreover, the degree of digitalization varies significantly according to firm size, with SMEs (firms with less than 200 employees) being less digitalized than large firms.

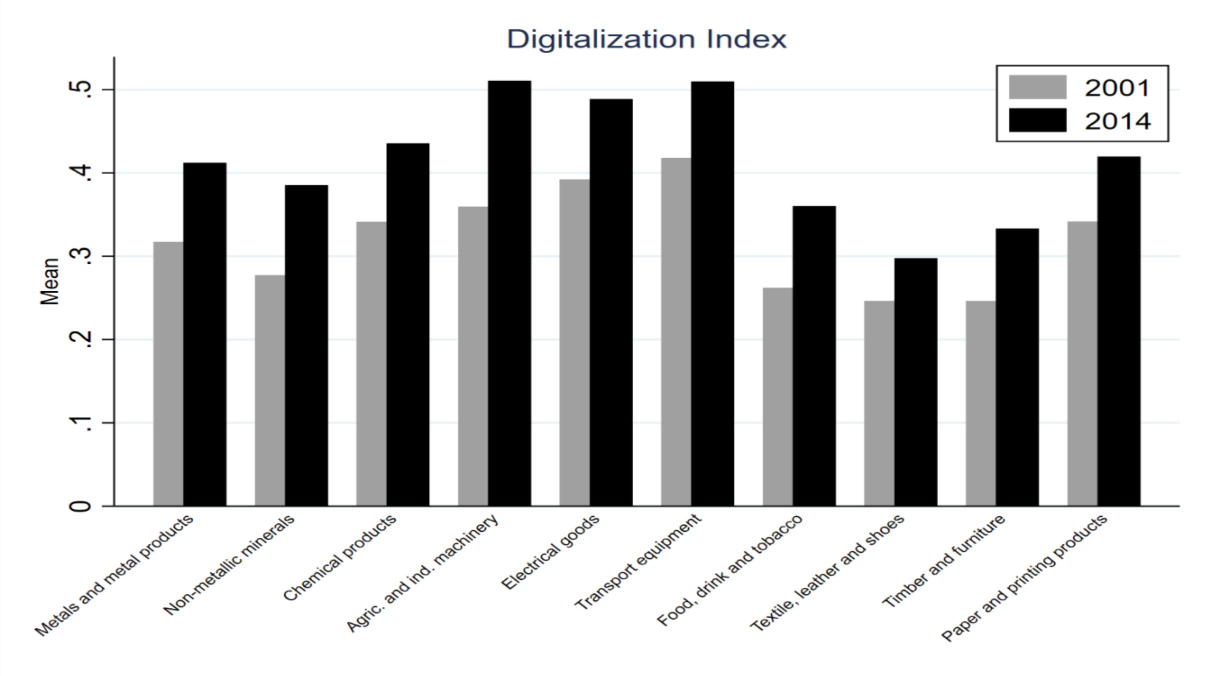
Figure 2.1: The digital transformation in the Spanish manufacturing sector



Source: ESEE survey and own elaboration.

Figure 2.2 shows the digital transformation by industry from 2001 to 2014. All sectors have endured a process of digitalization, which for some industries, such as agricultural and industrial machinery, and transport equipment has been remarkable. By 2014, the most digitalized industries are transport equipment, agricultural and industrial machinery, and the electrical goods sectors. In contrast, textiles, timber and furniture, and food, beverages, and tobacco are among the least digitalized industries. This is in line with the taxonomy presented by Calvino *et al.* (2018) at the industry level.

Figure 2.2: The digital transformation by industry (2001-2014)



Source: ESEE survey and own elaboration.

2.4.3. Descriptive Statistics

Table 2.2 shows the percentage of observations in the overall sample of SMEs contained in each category according to the export and import activities of the firm. We notice that the percentage of observations corresponding to SMEs that export over the period 2001-2014 is about 60%; while those that do not export equals 40%. Similar percentages are obtained when considering non-importers and importers.

Table 2.2: Observations in the sample by export activity

	All firms	Non-Exporters	Exporters	Non-Importers	Importers
Size class	Observations	Observations	Observations	Observations	Observations
SME	12,783	5,067	7,716	5,109	7,676
%	100%	39.64%	60.36%	39.95%	60.05%

Note: size class is defined in terms of the average number of employees of the firm: SME (< 200 employees). The sample is firms that are at least observed for two consecutive years and for which an estimate of TFP can be obtained.

In Table 2.3, descriptive statistics for the variables of interest are presented, including the export and import propensity, the digitalization index (DIG), and variables that reflect the structural characteristics of the firms of the sample. Here, we first compare SMEs that export in a given period with a sub-sample of SMEs that do not export and for which we can obtain an estimate of TFP. The exporters are, on average, larger, more productive, more innovative, with more human capital, and with a higher stake of foreign ownership. More interestingly, we see that exporters are more digitalized on average than non-exporters. Moreover, exporting SMEs have a lower relative markup than non-exporters. This may be because exporting SMEs may face a tougher competitive environment in foreign markets than their peers serving only the domestic market. As a consequence, they have to set lower markups in order to remain competitive relative to the more efficient foreign competitors. Second, we compare importers to non-importers on the same characteristics. Similar to exporters, firms that import are, on average, more digitalized, larger, more productive, more innovative, with more human capital, with a higher stake of foreign ownership, and with lower mark-ups.

Table 2.3: Descriptive statistics for exporters and non-exporters

	Exporters		Non-exporters		Importers		Non-importers	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Export propensity	1.00	0.00	0.00	0.00	0.81	0.39	0.30	0.46
Import propensity	0.80	0.40	0.29	0.45	1.00	0.00	0.00	0.00
DIG	0.38	0.17	0.25	0.15	0.38	0.17	0.26	0.16
TFP*	3.77	1.06	3.66	1.00	3.81	1.08	3.62	0.96
Markup	0.99	0.32	1.25	0.85	0.97	0.31	1.28	0.84
R&D propensity	0.37	0.48	0.09	0.28	0.38	0.48	0.09	0.28
Human capital	0.14	0.14	0.08	0.12	0.14	0.14	0.09	0.12
Age	32.02	21.31	25.57	18.82	32.00	21.67	25.65	18.24
Size	71.74	60.22	33.06	35.78	73.65	61.47	30.49	29.12
Foreign capital	0.14	0.35	0.02	0.14	0.15	0.35	0.01	0.12
Appropriability	0.04	0.20	0.01	0.11	0.04	0.20	0.01	0.11
Recessive market	0.32	0.47	0.34	0.47	0.33	0.47	0.33	0.47
Expansive market	0.21	0.41	0.15	0.36	0.21	0.41	0.16	0.36
Market competitors	0.20	0.40	0.21	0.41	0.21	0.41	0.19	0.39
External FC	4.26	3.43	3.88	3.16	4.30	3.44	3.83	3.14
Internal FC	6.21	2.40	5.80	2.45	6.19	2.41	5.84	2.45
Observations	7,716		5,067		7,676		5,107	

Source: ESEE 2001-2014.
Notes: s.d. stands for standard deviation. The sample is small and medium-sized firms (with less than 200 employees) that are at least observed for two consecutive years and for which an estimate of TFP can be obtained. * variables in logs.

2.5. Results

We now turn to assess the direct and indirect impact of digitalization on the export and import decision of SMEs. We will consider the direct effect attributed to the use of DTs, once we control for the indirect impact via TFP. As stated above, two conditions must be met for the existence of the indirect effect. First, the digitalization index must have a positive significant effect on TFP. Second, the coefficient of TFP in the export and import participation equations should be positive and significant. Therefore, the initial step for the analysis of the indirect effect is the endogenous Markov process presented in equation (2.11). The results of estimating this dynamic equation by system-GMM are presented in Table 2.4. The optimal lag length of the dependent variable is selected until no serial correlation is achieved in residuals. This implies that, although not reported, all specifications include the second lag of the TFP and that longer lags are used as instruments. All the specifications provide suitable results for the Hansen test of overidentifying restrictions[37] (testing for instruments validity) and for the non-serial correlation of the error terms[38].

First, the results in column (1) and (2), that assume the digitalization index (DIG) is predetermined and endogenous, respectively, support the assumption that digitalization enhances TFP. In column (3) we distinguish two dimensions within the digitalization index: the automation index, and the ICT index, which capture the effect of two distinct types of DTs. Both also exert a positive impact on TFP. The results in column (4) confirm the enhancing effect of digitalization after controlling for other firm characteristics that influence TFP. Therefore, the overall results displayed in Table 2.4 show that digitalization has a positive and significant impact on TFP and TFP growth (column 5), hence the first condition for the presence of the indirect effect is satisfied. Indeed, the results in column (4) show that for every one standard-deviation increase of the digitalization index, TFP is boosted by approximately 0.8%. This implies that, if we find evidence of a positive effect of TFP on exports and/or imports, we can conclude an indirect effect of digitalization on trade via TFP. Then, the estimation of the system of equations in (2.6) will provide the final proof. We, however, find no “learning by trading” effect in the case of SMEs, as the trade status coefficient appears non-significant (De Loecker, 2013).

[37] The null hypothesis of the Hansen test is that all overidentifying restrictions are jointly valid. As the p-values of the Hansen test are greater than 0.1, we cannot reject the null and this implies that the instruments are valid.

[38] For the disturbances to be not serially correlated, there should be evidence of significant negative first order serial correlation and no evidence of second order serial correlation in the differenced residuals. Hence, according to the Arellano-Bond test for serial correlation presented in Table 3.2, all models show evidence of significant first-order serial correlation in differenced residuals, and none show evidence of second-order serial correlation in the differenced residuals, suggesting the overall consistency of our estimates.

Table 2.4: The effect of the digitalization index on TFP

Dependent variable:	TFP	TFP	TFP	TFP	TFP growth
	(1)	(2)	(3)	(4)	(5)
TFP_{t-1}	0.516***	0.449***	0.430***	0.381***	-0.619***
	(0.178)	(0.141)	(0.127)	(0.106)	(0.106)
DIG_{t-1}	0.085***	0.134***		0.082**	0.082**
	(0.033)	(0.043)		(0.041)	(0.041)
$Automation_{t-1}$			0.037**		
			(0.015)		
ICT_{t-1}			0.103**		
			(0.050)		
Trade $status_{t-1}$				0.021	0.021
				(0.021)	(0.021)
Firm controls	No	No	No	Yes	Yes
Time & Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	9,058	9,058	9,058	9,056	9,056
Firms	1,487	1,487	1,487	1,486	1,486
No. of instruments	68	111	145	214	214
AR(1) test (p-value)	0.000	0.000	0.000	0.000	0.000
AR(2) test (p-value)	0.476	0.764	0.714	0.661	0.661
Hansen-J (p-value)	0.106	0.335	0.428	0.399	0.399

Notes: The dependent variable in columns (1) to (4) is the log of TFP, whereas in (5) it is the difference of the log of TFP from *t*-1 to *t*. All explanatory variables are included with one-period lag. All specifications include the second lag of TFP, industry dummies, and year dummies. Firm controls include employment, firm's age and foreign ownership. Estimates are obtained through the two-step system GMM estimator with robust standard errors corrected for finite sample bias (Windmeijer, 2005).AR(1) and AR(2) values report the p-values of the tests for first and second order serial correlation in the differenced residuals, respectively. In column (1) DIG is considered exogenous, while in the rest it is considered endogenous. The Hansen test of over-identification is under the null hypothesis that all of the instruments are valid. We use levels of TFP, DIG, Automation, ICT, trade status and employment dated (*t*-3) to (*t*-6) as instruments in the difference equation, and differences dated (*t*-2) as instruments in the levels equation, as well as age, foreign ownership, industry dummies and year dummies. Year FE only enter in the equation in levels. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 2.5 provides the estimation results of the export and import decision under different specifications of equation (2.6). Results are presented as average marginal effects (AME, henceforth). The potential interdependency between export and import participation is ignored in the first specification (columns 1 and 2). Thus, this specification is estimated as two separates RE dynamic probit models with the Wooldridge (2005) approach. The interdependence between both strategic decisions is considered in the second specification (columns 3 and 4), but the potential endogeneity of the digitalization index is ignored. This second specification is estimated as a RE dynamic bivariate probit model. As expected, the results of this specification confirm that the export and import strategies are not independent. The statistically significant estimated correlation coefficient for the error terms (ρ-value = 0.391) demonstrated this. This explains why a bivariate model, rather than two separate probit models, was chosen as the correct specification for each trading decision.

Finally, in the third specification (columns 5 and 6 in Table 2.5), an instrumental-variable CF approach is adopted to account for the potential endogeneity of the digitalization index to explain the decisions to export and import. Before examining the results, it is important to note that to avoid further simultaneity problems, all the independent variables are lagged one period. Although not reported, all specifications control also for sector dummies at the two-digit CNAE level to capture different technological opportunities and other unobserved factors varying across industries; and a set of time dummies capturing business cycle effects. As stated above, the first step of the CF approach consists of regressing the digitalization index on the instruments (the second lag of the digitalization and the industry regulatory index in communications) and the rest of exogenous variables in a fixed effect model. Although, for ease of exposition, the estimates of the first-stage regression are not shown, the coefficient of the second lag of the digitalization index is significantly positive and the regulation index is significantly negative, as expected. However, we cannot reject that the residual from this first-stage is statistically different from zero in the export and import participation equations, suggesting that endogeneity is not driving our results.

In what follows, and after ruling potential reverse causality problem between the digitalization index and trade participation decisions, we proceed to discuss in detail our estimation results on the main variables of interest based on columns 3 and 4. Concerning the main variable of interest, the digitalization index, we notice that it has a direct positive significant effect on the probability to export and import. To be more specific, the marginal effect implies that an increase of the digitalization index by 10% raises the corresponding probability to export by almost 0.9 percentage points, holding all other variables constant. Hence, digitalization appears to facilitate the internationalization of SMEs by reducing transaction costs, for instance, those related to marketing or entry-related cost, which allow SMEs to engage in foreign sales. Similarly, concerning imports, an increase of 10% of the digitalization index appears to increase the probability to import by about 0.5 percentage points. In this regard, the results suggest that digitalization directly facilitates trade in Spanish manufacturing SMEs, although the effect seems to be larger for exports than for imports.

Table 2.5: The effect of digitalization on SMEs trade. Marginal effects

	RE Probit		RE Biprobit		RE Biprobit & CF	
	Export	Import	Export	Import	Export	Import
	(1)	(2)	(3)	(4)	(5)	(6)
DIG	0.107***	0.059**	0.090***	0.049**	0.072***	0.077**
	(0.025)	(0.027)	(0.020)	(0.023)	(0.026)	(0.031)
TFP_{t-1}	0.045**	0.089***	0.038**	0.079***	0.029*	0.085***
	(0.018)	(0.023)	(0.016)	(0.020)	(0.016)	(0.021)
Export $status_{t-1}$	0.198***	0.050***	0.163***	0.051***	0.188***	0.051***
	(0.012)	(0.008)	(0.011)	(0.008)	(0.011)	(0.009)
Import $status_{t-1}$	0.035***	0.205***	0.033***	0.185***	0.033***	0.197***
	(0.008)	(0.012)	(0.007)	(0.011)	(0.007)	(0.011)
Relative $Markup_{t-1}$	-0.028***	-0.075***	-0.023***	-0.068***	-0.022**	-0.067***
	(0.010)	(0.015)	(0.009)	(0.011)	(0.009)	(0.012)
$R\&D_{t-1}$	0.013	0.023**	0.010	0.022**	0.009	0.020**
	(0.009)	(0.010)	(0.007)	(0.009)	(0.008)	(0.009)
Human $Capital_{t-1}$	0.047*	0.037	0.040*	0.033	0.048**	0.027
	(0.028)	(0.028)	(0.024)	(0.029)	(0.024)	(0.030)
Age_{t-1}	0.005	0.002	0.004	0.002	0.006	-0.000
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
$Size_{t-1}$	0.244**	0.546***	0.194***	0.488***	0.182**	0.453***
	(0.098)	(0.106)	(0.074)	(0.096)	(0.075)	(0.100)
Foreign $Capital_{t-1}$	0.019	0.040**	0.015	0.035**	0.019	0.035**
	(0.017)	(0.017)	(0.012)	(0.016)	(0.013)	(0.016)
Recessive $Market_{t-1}$	-0.003	-0.007	-0.003	-0.005	-0.003	-0.008
	(0.007)	(0.008)	(0.006)	(0.007)	(0.006)	(0.007)
Expansive $Market_{t-1}$	0.007	0.015*	0.006	0.013*	0.004	0.009
	(0.008)	(0.009)	(0.007)	(0.008)	(0.007)	(0.009)
$Competitors_{t-1}$	-0.013	0.004	-0.011	0.004	-0.006	0.008
	(0.009)	(0.009)	(0.007)	(0.009)	(0.008)	(0.010)
$Appropriability_{t-1}$	0.052**	0.008	0.044**	0.008	0.042**	-0.003
	(0.022)	(0.018)	(0.018)	(0.020)	(0.019)	(0.020)
External $Finance_{t-1}$	-0.000	0.001	-0.000	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Internal $Finance_{t-1}$	-0.000	0.000	-0.000	0.000	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Rho			0.391***	0.391***	0.363***	0.363***
			(0.061)	(0.061)	(0.063)	(0.063)
Residual[a]					0.012	-0.055
					(0.041)	(0.048)
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Initial Condition	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak Means	Yes	Yes	Yes	Yes	Yes	Yes
IV CF					Yes	Yes
Observations	9,182	9,145	9,143	9,143	8,322	8,322
Log-Likelihood	-1,558.22	-2,035.12	-3,567.62	-3,567.62	-3,214.14	-3,214.14

Notes: We report marginal effects at sample means. All specifications include industry and year dummies. All specifications include the initial condition and the within-means of internal and external finance, which appear statistically significant. Specifications in (5) and (6) include the residual from a first step of an IV control function approach in which the regulation index and the second lag of DIG are used as instruments for DIG in *t*. [*] Significant at 10%, [**] significant at 5%, [***] significant at 1%. [a] Rivers-Vuong (1988) endogeneity test.

Concerning the indirect effect (through TFP enhancement) that digitalization may play in trade activities, the results in Table 2.5 provide also support. TFP has both a significant effect on the export and import propensity. Therefore, our results support the argument that digitalization enhances the probability to participate in exports and imports not only through a direct channel but also through productivity gains. Hence, TFP appears as significant and positive in the export and import equation. Particularly, the marginal effects show that an increase of 10% in TFP raises the export probability by 0.4 percentage points, and the import probability by 0.8 percentage points. This is also consistent with the self-selection hypothesis (Melitz, 2003). Firm's productivity affects its decision to participate in international markets (i.e., importing inputs and/or exporting output).

As expected from previous studies (Elliot *et al.*, 2019; Exposito and Sanchis-Llopis, 2021), past export and import experiences stand as important determinants of actual export and import propensities, respectively. This suggests that there are important sunk costs into internationalization. In other words, once a firm has paid the sunk costs of being global, it is easier to pursue its export or import activities in the next period. Indeed, everything else being equal, SMEs exporting in period *t-1* vis-à-vis non-exporters, are about 16 percentage points more likely to continue exporting in period *t*. Similarly, SMEs importing in period *t-1* are 19 percentage points more likely to import in period *t* with respect to non-importers in *t-1*. Moreover, we show that previous import experience also has a positive effect on export participation and vice-versa, implying the existence of learning effects due to previous internationalization strategies. Importing firms have access to a greater variety of cheaper (or better quality) intermediate inputs allowing them to improve their productivity (or increase the quality of their products) and break into export markets (Kasahara and Rodrigue, 2008; Bas and Strauss-Kahn, 2014). Firms that import in period *t-1* are 3.3 percentage points more likely to export in period *t* with respect to non-importers in *t-1*, whereas previous export experience raises the probability of importing in period *t* by 5.1 percentage points. Therefore, through exporting, firms can access knowledge about the needs of global markets and potential suppliers, translating into productivity improvements (Bernard *et al.*, 2018) and/or lower import costs, which subsequently enables firms to source from foreign markets.

In terms of the rest of the control variables, the results displayed in Table 2.5 show that, ceteris paribus, SMEs with lower relative markups have a higher probability to participate in exporting and importing. Additionally, human capital, appropriability conditions, and firm size have also a positive and significant effect on export propensity, whereas R&D, foreign ownership, firm size and an expansive market demand appear as positive and significant in the import equation. Despite not being reported, the initial condition appears positive and significant in all the specifications. The rest of the firm-level controls do not seem to affect the decision of SMEs to enter into foreign markets.

2.5.1. Robustness Analysis

In this section, we perform some robustness tests to check if the results we have obtained are robust to some different specifications of the model. The results are displayed in Table 2.6 where, for clarity reasons, we present only the average marginal effects of the digitalization index (DIG) and that of the TFP[39].

As discussed above, in the previous specifications the unobserved firm-specific effect has been modeled using only the individual time means of the internal and external financial variables. While such restrictions may help to avoid the multicollinearity problem, they can also cause biases (Semykina, 2018). As a first robustness check, we include all the within-means of the control variables for the different specifications of our model to avoid potential biases. Having a look at the results in column (1) of Table 2.6, we perceive that digitalization still shows a positive and significant effect on export participation. This effect is to raise the probability to export by roughly 0.9 percentage points for an increase of 10% of the digitalization index. TFP remains also significant, confirming the indirect effect. Moving to the second column, the results show similar results than in Table 2.5. Indeed, we have evidence of both a direct and indirect effect of digitalization on import propensity. However, the direct effect is of a lower magnitude, i.e., raising the digitalization index by 10% increases the probability of importing by only 0.4 percentage points.

Second, we follow Mañez *et al.* (2020) and model the unobserved firm's heterogeneity terms, α_i, conditional on the pre-sample mean of the dependent variable, as follows:

[39] Although all specifications include the same controls as in Table 2.5, for ease of exposition only the results for the variables of interest are presented. Full results are available from the authors on request.

$$\alpha_i^{exp} = \delta_o^{exp} + \delta_r^{exp}\overline{EXP_{i98-99}} + u_i^{exp} \tag{2.12}$$

$$\alpha_i^{imp} = \delta_o^{imp} + \delta_r^{imp}\overline{EXP_{i98-99}} + u_i^{imp} \tag{2.13}$$

The pre-sample mean $EXP_{i98\text{-}99}$ ($IMP_{i98\text{-}99}$) is calculated as the within-firm mean of *EXP* (*IMP*) for pre-sample years. As the dynamic nature of equation (2.1) implies that the period of analysis covers 2002-2014, we use the pre-sample period 1998–1999. Results are reported in columns (3) and (4), and despite the loss in observations, both the digitalization index and TFP remain positive and significant in explaining both the decision to export and import.

The next robustness check deals with a concern related to the fact that TFP in the trade equations is an estimated regressor, which could render the standard errors inaccurate and therefore affect inference. To address this problem, we report block bootstrapped standard errors with the firm as the block unit and based on 250 replications. The results are presented in columns (5) and (6) and are very similar to the baseline specification. According to column (5), digitalization and TFP have a positive and significant effect on export participation. In terms of import participation, the results in column (6) show that both digitalization and TFP also have a positive and significant effect on the decision to import.

For the final robustness check, instead of using the second lag of the digitalization index as instrument in the CF, we use the average (excluding the firm) of the digitalization index by year, industry, region, and R&D status. In this case, we assume that the extent of digitalization of the firm's counterparts influences its digital transformation but should not be correlated with the residual in the trade equation. Thus, in the first stage, we instrument the digitalization index using the average value of peers' digitalization and the same regulation index as in columns (5) and (6) of Table 2.5. Although not reported, the peers' digitalization has a positive effect on the digitalization index while the opposite holds regarding the effect of the regulation index. Looking at the results presented in columns (7) and (8) of Table 2.6, we notice that digitalization has a positive direct and indirect effects on both exports and imports.

Table 2.6: Robustness checks

	Wooldridge (2005)		**Mañez *et al.* (2020)**	
Dependent variable:	Export	Import	Export	Import
	(1)	(2)	(3)	(4)
DIG	0.088***	0.044*	0.108***	0.105***
	(0.021)	(0.024)	(0.025)	(0.031)
TFP_{t-1}	0.035**	0.068***	0.095***	0.145***
	(0.017)	(0.020)	(0.021)	(0.028)
Firm controls	Yes	Yes	Yes	Yes
Time & Industry FE	Yes	Yes	Yes	Yes
Initial Condition	Yes	Yes		
Mundlak Means (All)	Yes	Yes		
Pre-sample Mean $_{(98/99)}$			Yes	Yes
Bootstrapped 250 reps				
Observations	9,143	9,143	7,317	7,317
Log-Likelihood	-3,546.43	-3,546.43	-3,416.01	-3,416.01
	Bootstrapped s.e.		**Alternative IV**	
Dependent variable:	Export	Import	Export	Import
	(5)	(6)	(7)	(8)
DIG	0.090***	0.049*	0.100***	0.075**
	(0.022)	(0.027)	(0.027)	(0.032)
TFP_{t-1}	0.038**	0.079***	0.038**	0.079***
	(0.018)	(0.021)	(0.016)	(0.020)
Firm controls	Yes	Yes	Yes	Yes
Time & Industry FE	Yes	Yes	Yes	Yes
Initial Condition	Yes	Yes	Yes	Yes
Mundlak Means (All)				
Pre-sample Mean $_{(98/99)}$				
Bootstrapped 250 reps	Yes	Yes		
Observations	9,143	9,143	9,143	9,143
Log-Likelihood	-3,567.62	-3,567.62	-3,566.80	-3,566.80

Notes: We report marginal effects at sample means of the variables of interest. All specifications include the same control variables as in Table 2.5 together with industry and year dummies. Specifications in (1), (2), (5), (6), (7) and (8) include the initial condition and the within-means of internal and external finance, which appear statistically significant. Those are replaced by the pre-sample mean of the dependent variable in (3) and (4). In (5) and (6) we report block bootstrapped standard errors (s.e.) at firm level in parentheses (250 replications). Specifications in (7) and (8) include the residual from a first step of an IV control function approach in which the regulation index and the average (excluding the firm) of the digitalization index by year, industry, region and R&D status are used as instruments for DIG in *t*. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Therefore, the effect of digitalization on the propensity to export and import seems to be confirmed by the robustness checks we have performed. We also have evidence of a positive and significant effect of TFP. Overall, our results indicate that the extent of firms' digitalization facilitates both exports and imports, both directly and indirectly through TFP enhancement.

2.5.2. Sensitivity Analysis

At this stage, we have shown that digitalization has a significant and positive direct effect on the export and import participation of Spanish manufacturing SMEs, as well as an indirect effect through the TFP channel. Now, our purpose is to examine which firms and industries benefit most from digitalization. Previous studies have shown that the relationship between DTs and firm performance is heterogeneous, with some firms being more successful in exploiting DTs than others (DeStefano *et al.*, 2018).

Thus, considering that the take-up of DTs varies widely across industries, we first perform the analysis distinguishing between firms belonging to high- and low-digitalized industries according to the classification by Calvino *et al.* (2018) (see Table 2A.2). In principle, it is unclear whether the trade effect of digitalization is greater for firms in low-digitized industries or vice-versa. While firms in low-digitized industries have more to gain from the adoption of DTs, the digital transformation may be more effective when many firms in an industry use DTs intensively because of the potential for knowledge spillovers (Laursen and Meliciani, 2010).

The trade impact of the digitalization index and TFP in low-digitalized industries (columns 1 and 2) and in high-digitalized industries (columns 3 and 4) is displayed in Table 2.7. The results suggest that DTs in low-digitalized industries both directly facilities the entry into foreign markets and have an indirect effect through productivity gains. The direct effect implies that a 10% increase of the digitalization index boosts the probability of exporting by 8.5 percentage points, while raises the probability of importing by 5.2 percentage points. Digitalization appears to influence positively the export decision in high-digitized industries. For every 10% increase of the digitalization index, exports are expected to raise by 7.9 percentage points, whereas the indirect effect is not statistically significant. The decision to import is only indirectly affected by digitalization through TFP. While firms in highly digitalized industries still appear to benefit from the use of DTs, it is precisely in more digitally disadvantaged sectors where SMEs can gain more from the use of DTs, both directly and indirectly through TFP gains.

Secondly, DTs have been linked to the fragmentation of the global value chain (GVC) and the decision to offshore and outsource as they reduce the transaction and adjustment costs of moving some activities outside the firm (Abramovsky and Griffith, 2006; Rasel, 2017). At the same time, SMEs are under-represented in GVCs, and DTs may open up new avenues for them to play a more active role (Sasidharan and Reddy, 2021). Given that the integration in GVCs varies greatly across industries, we perform the analysis distinguishing between firms in sectors that are low- and highly-integrated in GVCs (see Table 2A.2). In this case, the classification on GVC participation is based on the OECD "GVC forward linkage" indicator at industry level for Spain for the year 2000, which is expressed as the share of domestically produced inputs used in third countries' exports.

Table 2.7: Sensitivity analysis. Digitalization and GVC participation by sector

	Low-Digitalized		**High-Digitalized**	
	Export	Import	Export	Import
	(1)	(2)	(3)	(4)
DIG	0.085***	0.052*	0.079**	0.050
	(0.023)	(0.029)	(0.037)	(0.039)
TFP_{t-1}	0.045**	0.077***	0.023	0.086***
	(0.019)	(0.026)	(0.029)	(0.032)
Firm controls	Yes	Yes	Yes	Yes
Time & Industry FE	Yes	Yes	Yes	Yes
Initial condition	Yes	Yes	Yes	Yes
Mundlak means	Yes	Yes	Yes	Yes
Observations	5,624	5,624	3,519	3,519
Log-Likelihood	-2,096.00	-2.096.00	-1,425.79	-1,425.79
	Low-GVC		**High-GVC**	
	Export	Import	Export	Import
	(5)	(6)	(7)	(8)
DIG	0.115***	0.028	0.076***	0.069**
	(0.035)	(0.040)	(0.024)	(0.029)
TFP_{t-1}	0.056**	0.057**	0.008	0.116***
	(0.025)	(0.029)	(0.022)	(0.029)
Firm controls	Yes	Yes	Yes	Yes
Time & Industry FE	Yes	Yes	Yes	Yes
Initial condition	Yes	Yes	Yes	Yes
Mundlak means	Yes	Yes	Yes	Yes
Observations	3,524	3,524	5,619	5,619
Log-Likelihood	-1,473.99	-1,473.99	-2047.13	-2047.13

Notes: The classification on digitalization is based on Calvino *et al.* (2018). The classification on GVC-integration is based on the GVC forward linkage indicator provided by the OECD for Spain. We report marginal effects at sample means of the variables of interest. All specifications include the same control variables as in Table 2.5 together with industry and year dummies. All specifications include the initial condition and the within-means of internal and external finance, which appear statistically significant. * Significant at 10%, ** significant at 5%, *** significant at 1%.

The trade impact of the digitalization index and TFP in industries with low-participation (columns 5 and 6) and in high-participation in GVCs (columns 7 and 8) is displayed in Table 2.7. The results show that in low-GVC integrated sectors, digitalization exerts a direct and indirect impact on exports, while digitalization increases the probability to import just through the productivity effect. In the case of industries with high participation in GVCs, digitalization directly increases the probability to export, but there is no indirect effect through productivity. In contrast, digitalization has a direct and indirect impact on imports.

Table 2.8: Sensitivity analysis. ICTs vs. automation

	Export (1)	Import (2)
ICT	0.086***	0.054**
	(0.019)	(0.022)
Automation	0.012	0.002
	(0.011)	(0.012)
TFP_{t-1}	0.038**	0.079***
	(0.016)	(0.020)
Firm controls	Yes	Yes
Time & Industry FE	Yes	Yes
Initial condition	Yes	Yes
Mundlak means	Yes	Yes
Observations	9,143	9,143
Log-Likelihood	-3565.27	-3565.27

Notes: We report marginal effects at sample means of the variables of interest. All specifications include the same control variables as in Table 2.5 together with industry and year dummies. All specifications include the initial condition and the within-means of internal and external finance, which appear statistically significant. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Finally, while both automation and ICTs will bring productivity gains to the firm, it seems plausible that the direct effect of these technologies on trade may be different. Although both are derived from the same technologies, they potentially have quite different implications for the international division of labor and trade activities. On the one hand, automation technologies -including robots and CAD- are more likely to reduce the number of tasks and may accelerate the substitution of humans by machines, and thus, they are likely to induce “reshoring” of some tasks previously outsourced. On the other hand, ICTs, particularly communication technologies (Baldwin, 2016), help to overcome physical distance, reduce matching and coordination costs, and thus, are likely to encourage fragmentation of the production processes, leading to more trade. To assess this, we estimate the system of equations (2.6) distinguishing two dimensions within the digitalization index: the automation index, and the ICT index. The results, presented in Table 2.8, show that while the ICT index appears positive in explaining both the export and import participation decisions, the automation index does not play a significant direct role. This coincides with the fact that ICT technologies are more likely to reduce costs associated to physical distance than automation technologies. Indeed, ICTs support distance reduction between the seller and the buyer by decreasing the costs of searching, matching and communicating, the costs of moving inputs and outputs, and the costs of management and monitoring (Venables, 2001). All these cost reductions promoted by ICTs, as they help to overcome physical distance, are expected to increase the fragmentation of the production process and therefore have a positive impact on both exports and imports. Nevertheless, the productivity effect of both ICT and automation leads to a higher probability to import and export. The results for the effect of ICT and automation on imports are in line with previous studies that suggest that digitalization, and automation, did not cause reshoring in Spanish firms (see Alguacil-Marí *et al.*, 2022; Stapleton and Webb, 2020).

2.6. Conclusion

DTs have been considered to exert an important role in facilitating trade because of their potential to reduce transaction costs and improve communications between buyers and sellers, but also owing to their ability to enhance firms' efficiency. Thus, DTs may help SMEs to overcome the barriers they face to enter into foreign markets. In this study we analyze both the direct and indirect effect (via productivity) of the digital transformation on both the export and import participation of SMEs. Unlike previous studies that use a single indicator of the digitalization phenomenon, we use a synthetic index of digitalization at the firm level that considers the multi-faceted phenomenon of the digital transformation and hence considers potential complementarities between different DTs. Then, we study both the direct effect of digitalization on the import and export participation decisions of SMEs, as well as the indirect effect through enhanced productivity. To unravel the indirect effect, we consider an endogenous Markov process for the dynamics of TFP.

Our main empirical strategy consists of estimating a dynamic RE bivariate probit model that models the decision to export and import simultaneously. An important feature of the model is that we consider previous import activity when examining the determinants of firms' decision to export and vice-versa. We use a sample from the ESEE database of manufacturing SMEs in Spain from 2001 to 2014. Our findings suggest that the degree of digitalization in SMEs exerts a direct positive effect on the decision to trade. Moreover, import and export participation increases with digitalization also through productivity enhancements (i.e., the indirect TFP channel). In addition, the direct effect seems to be larger for exports than for imports, while the opposite seems true for the indirect effect. This means that the same percentage increase in firms' digitalization has, on average, a greater increase in the probability of exporting than importing. Conversely, the same percentage increase in TFP increases the probability of importing more than exporting. Moreover, our results show that importing and exporting are complementary. Therefore, policies that difficult importing of foreign intermediates, such as tariff and non-tariff barriers, can have a large adverse effect on exporting final goods, causing exports to fall significantly.

Our findings offer important insights to entrepreneurs and managers of SMEs. By investing in the process of digitalization, SMEs may improve their likelihood to enter into foreign markets and become more efficient and integrated in GVCs, which reinforces the effect of digitalization upon export and import participation. From a policy standpoint, our findings highlight the importance of encouraging the adoption and efficient use of DTs by SMEs. As the results suggest, this will increase the export base in Spain, which has previously been shown to be small. Thus, our findings point to a need for policymakers to provide not just the necessary digital infrastructure but also, to offer incentives, well in the form of subsidies, tax breaks or training courses, in order to promote the adoption and efficient use of DTs.

Nevertheless, this study is not without limitations, which provide interesting avenues for future research. For instance, we have no information on new Industry 4.0 technologies, such as 3D printing, cloud computing, artificial intelligence, machine learning, or blockchain. The availability of data on these technologies will allow for a more comprehensive state of the real digital transformation and how it affects trade activities. Furthermore, data on the firms' export destinations and import origins might allow us to test the hypothesis of the effect of digitalization on the *death of distance* (Cairncross, 2002), where digitalization helps to remove traditional geographical barriers and makes it more accessible to export and import from and to anywhere in the world. Still, caution should be used regarding the generalizability of these results, and therefore, many questions regarding policy implications are still open.

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APPENDIX 2.A

Table 2A.1: Description of the variables

Variable	Description
Export propensity	Dummy=1 if the firm exports; =0 otherwise.
Import propensity	Dummy=1 if the firm imports; =0 otherwise.
DIG	Digitalization index that ranges from 0 to 1 (see Appendix 2.B).
TFP	The logarithm of the total factor productivity is estimated as in the methodology section.
Relative Markup	The ratio of *P/MC* of the firm relative to the average markup of the industry. Obtained as in De Loecker and Warzynski (2012)
R&D	Dummy=1 if the firm conducts R&D activities; =0 otherwise.
Human capital	% of employees with a degree.
Age	The logarithm of the age of the firm.
Size	The number of employees.
Foreign capital	Dummy=1 if the firm has foreign capital participation; =0 otherwise.
Appropriability	Dummy=1 if the firm has registered patents either in Spain or abroad, and/or utility models; =0 otherwise.
Recessive market	Dummy= 1 if the firm faces a recessive market demand; =0 otherwise.
Expansive market	Dummy= 1 if the firm faces an expansive market demand; =0 otherwise.
Competitors	Dummy= 1 if the number of competitors reported by the firm is less than 10; =0 otherwise.
External Finance	It reflects the firm's access to internal funds and it is obtained as explained in the methodology section.
Internal Finance	It reflects the firm's access to external funds and it is obtained as explained in the methodology section.

Note: see Table 1A.2 in Appendix 1.A for the description of variables used for the estimation of the production function**.**

Table 2A.2: Division by industries

Industries	High digitalized	Low digitalized	High integrated in GVCs	Low integrated in GVCs
1. Metals and metal products		✓	✓	
2. Non-metallic minerals		✓		✓
3. Chemical products		✓	✓	
4. Agric. and ind. machinery	✓		✓	
5. Electrical goods	✓		✓	
6. Transport equipment	✓		✓	
7. Food, drink, and tobacco		✓	✓	
8. Textile, leather, and shoes		✓		✓
9. Timber and furniture	✓			✓
10. Paper and printing products	✓			✓

Note: "*High digitalized*" identifies sectors classified in terms of digital intensity as High and Medium-high in Calvino *et al.* (2018), while "*Low digitalized*" refers to sectors classified as Low and Medium-low. "*High integrated in GVCs*" identifies sectors that have a GVC forward linkage index (based on *EXGR_DVAFXSH for Spanish industries in the year 2000*) above the average of all manufacturing sectors. "*Low integrated in GVCs*" refers to sectors that have a GVC forward linkage index below the average.

APPENDIX 2.B

2.B.1. The Dimensions of the Digitalization Index

The demand for useful data and measurement tools relating to the ongoing and accelerating digital transformation is particularly acute due to the broad role that DTs play in economies and businesses in particular. Moreover, DTs are interrelated, with the effect of one technology being enhanced by the use of other DT (Bartelsman *et al.*, 2017). Therefore, the effectiveness of DTs should be assessed as a whole and not individually. Under these premises, we construct a synthetic indicator of digitalization at firm level based on the work of Calvino *et al.* (2018) but adapted according to the data available in the ESEE. This implies that instead of using a single indicator, we use several dimensions of the digital transformation to represent the extent of digitalization of firms in Spain. In doing so, we use the ESEE dataset. However, although the ESEE covers the period from 1990 to 2014, some of the variables required for our index are only available since 2000 or 2001. Therefore, the final digitalization index is built considering the 2001-2014 period.

Table 2B.1: Digitalization index by dimensions

Calvino *et al.* (2018) At the 2-digit industry level	**This study** At firm level
Technological components: - Investment in ICT equipment - Purchases of ICT services - Purchases of ICT goods	**Technological components:** - ICT capital - Computer programming services - Implementation of software programs
Digital-related human capital: - ICT specialists as a share of total employment	**Digital-related human capital:** - Personnel training in software and information technology
The extent of automation: - Robot stock	**The extent of automation:** - Use of robots - Use of computer-aided design - Use of flexible systems - Use of LAN
Interactions with stakeholders: - Share of turnover from online sales	**Interactions with stakeholders:** - Ownership of an internet domain - Ownership of a webpage - E-buying - Business to consumer e-commerce - Business to business e-commerce

Note: Author's elaboration

Hence, in the spirit of Calvino *et al.* (2018), the digitalization index consists of 4 dimensions and here it englobes 13 components. In Table 2B.1 we compare the differences between the index and its components used here and that of Calvino *et al.* (2018). Below, we discuss in detail the four dimensions and their components as well as provide some descriptive statistics for each of the components. We pay particular attention to the behavior of the components across firm size and industry.

1. Technological Components

The first dimension considered in the digitalization index is the technological components. We proxy this by focusing on ICT capital, computer programming services, and the implementation of software programs either hired or developed by the focal firm.

i) ICT Capital

Unlike Calvino *et al.* (2018), the ESEE does not provide information that allow us to draw a distinction between ICT tangibles, such as computers, and ICT intangibles, such as software. Instead, it provides data on investment in information processing equipment, which is available on an annual basis since 1990. Given the lumpiness in the investment data at firm level, we use instead the stock of ICT capital, a variable reflecting accumulated investments in information processing equipment. To obtain an estimate of the ICT capital stock we use the perpetual inventory method with a depreciation rate of 31.5% (EU-KLEMS) and deflating monetary units by the industry-level specific IT deflators for Spain from the EU-KLEMs database. Second, we compute the relative value of the ICT capital stock with respect to the industry-year average. Third, we classify this relative value according to the decile of the distribution to which the firm belongs. The result is that for each firm-year observation we end up with a new categorical variable ranging from one to ten, where ten corresponds to those firms with the largest relative stock of ICT capital. Finally, we normalize into a 0-to-1 scale.

ii) Software Programming Services

The ESEE provides information on the use of software programming services. This is a categorical[40] variable available since 1990 every 4 years. We proceed as follows: first, the variable is rescaled to show

[40] This variable has four categories: i) It does not use them, ii) performed by the company, ii) partially subcontracted, iii) totally subcontracted.

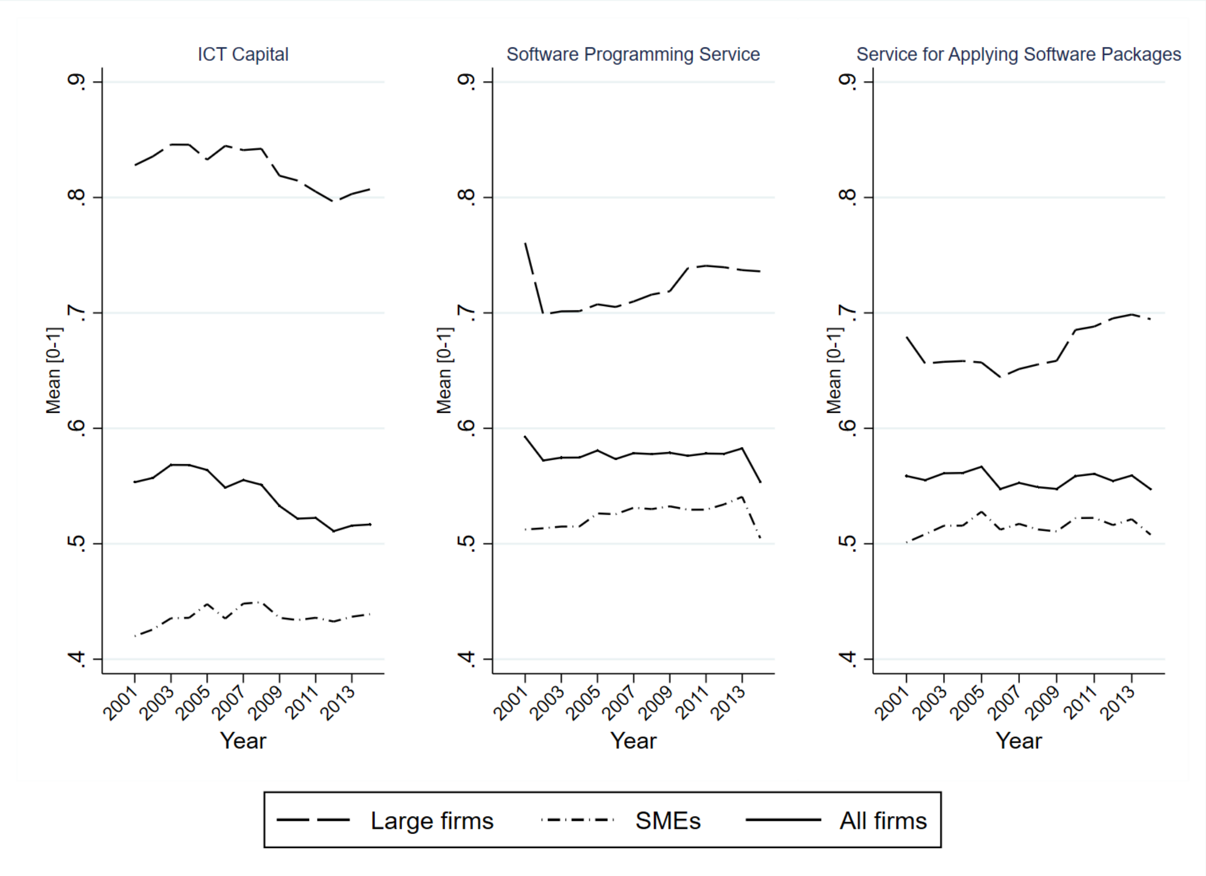
the degree of firm's digital capabilities. In this regard, it takes the value 0 if the firm does not use computer programming services, 1 if these services are totally contracted to another firm, 2 if they are partially contracted, and 3 if they are performed exclusively by the firm itself. Hence, we consider that performing computing programming services inhouse reflects a higher digital capability than contracting them. Second, to obtain an annual estimate we extrapolate the series by firm. Finally, we normalize into a 0-to-1 scale.

iii) Services for Applying Software Packages

Similarly, The ESEE provides information on the use of services for applying software programming services. This is also a categorical variable available since 1990 every 4 years that reflects the degree of implementation of software programs of common use (such as accounting, etc.). We proceed in the same way as the preceding indicator: we first re-scale to capture the degree of firm's digital capabilities, and then we extrapolate to obtain an annual estimate by firm. Finally, this is normalized into a 0-to-1 scale.

Figure 2B.1 shows the evolution between 2001 and 2014 of the three components of the technological components dimension for the whole sample, for SMEs and for large firms. ICT capital appears to have a fairly constant behavior. However, we observe a slight decline for the whole sample and large firms since the 2008 financial crisis. Without surprise, large firms seem to have, on average, twice as much ICT capital as SMEs, but experienced a larger decline as a consequence of the 2008 financial crisis. Concerning software programming services, its evolution has been fairly constant between 2001 and 2014, but it experiences a modest decline in all the subsamples. Interestingly, when it comes to the whole sample and SMEs, there is a relatively steep decrease in the last year of the period of analysis, which is not the case for large firms. Finally, as for services for applying software packages, we observe that while the behavior is quite stable for SMEs, large firms experience a decline until 2007, followed by a continuous increase until 2013. Between 2013 and 2014, we notice a decline in the series especially for the whole sample and SMEs, but less pronounced that in the software programming services.

Figure 2B.1: The technological components by firm size

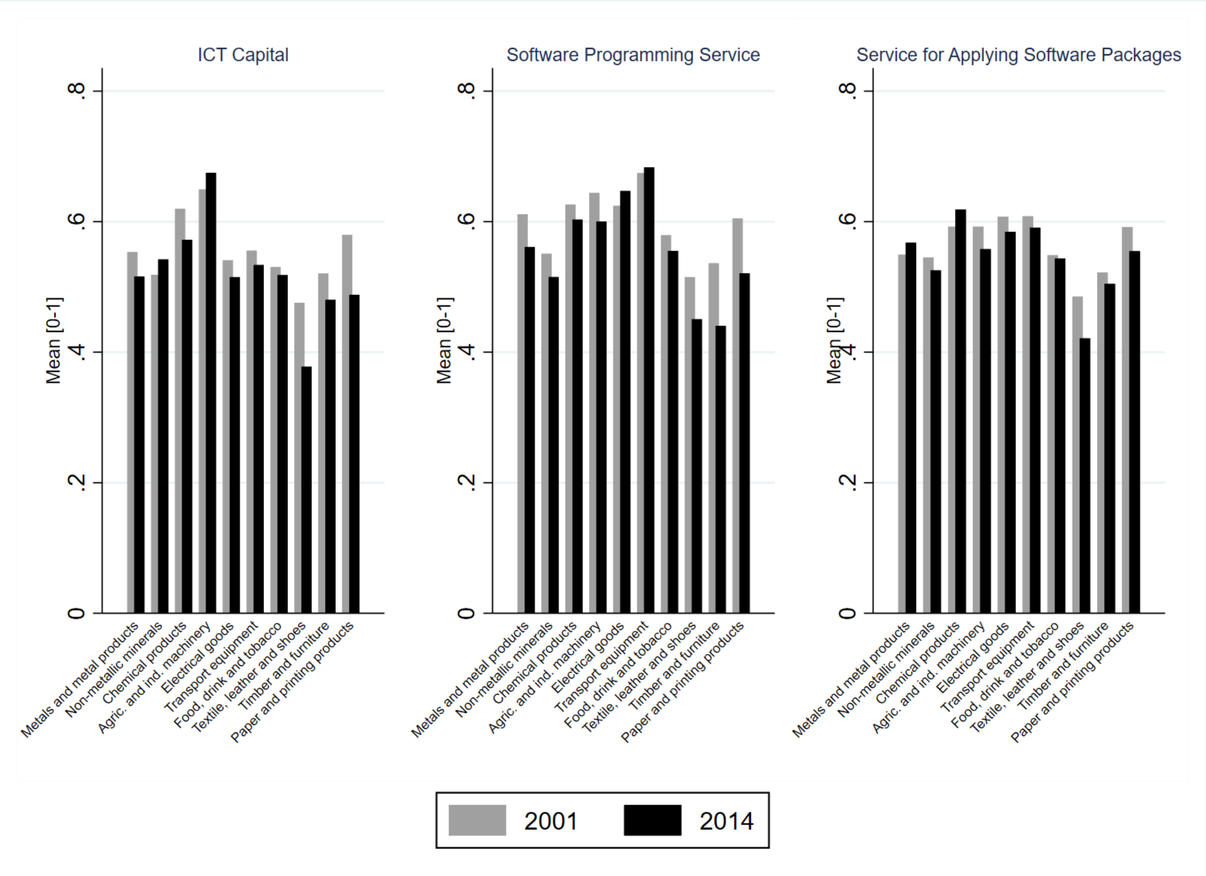


Source: ESEE survey and own elaboration.

Figure 2B.2 displays the three components of the technological components dimension for the 10 industries considered in our analysis in 2001 and 2014. Surprisingly, we observe that ICT capital in 2014 is, in almost all industries, lower than in 2001, which goes in line with Figure 2B.1. This may be due to a reduction in ICT investment because of the financial crisis, or a shift towards outsourcing of IT services. The agricultural and industrial machinery industry has the highest stock of ICT capital, while the timber, leather and shoes industry has the lowest. This is true regardless of whether we consider the year 2001 or 2014. The evolution of the other two components confirms that firms tend to outsource IT services, as most of the industries have experienced a decrease in these components. Indeed, the higher the value of these components, the more firms perform this kind of services themselves.

Looking at software programming service, the most digitalized industry is transport equipment, whereas the least digitalized is textile leather and shoes. Concerning service for applying software packages, the most digitalized industries in 2001 were electrical goods and transport equipment, whereas chemical products took the lead in 2014. As for the least digitalized industry, it is, once more, textile, leather and shoes, which also experience an important decline between 2001 and 2014.

Figure 2B.2: The technological components by industry



Source: ESEE survey and own elaboration.

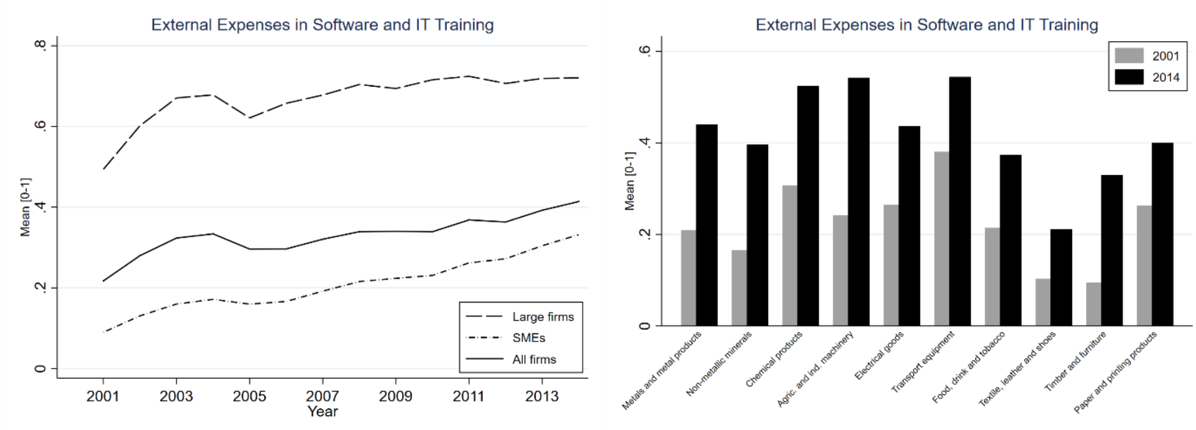
2. Digital-Related Human Capital

i) ICT Training Capital

The main measure of digital-related human capital is the expenses in ICT training, which is available on annual basis since 2001. First, monetary units are deflated using the price index for professional services drawn from EU-KLEMs database. Given the lumpiness in the expenses data at firm level, we first obtain an estimate of the accumulated stock of training built using the perpetual inventory method with a depreciation rate of 33% (Dewan and Kraemer, 2000). Second, we compute the relative value of ICT training capital with respect to the industry-year total. Then, we classify this relative value according to the decile of the distribution to which the firm belongs. The result is that for each firm-year observation we end up with a new categorical variable ranging from one to ten, where ten corresponds to those firms with the largest relative human capital in ICT. Finally, we normalize into a 0-to-1 scale.

The behavior of capital training in ICT is depicted in Figure 2B.3. The left panel shows the behavior over time for the whole sample, SMEs and large firms. Large firms and SMEs both seem to increase their expenses in ICT training. While SMEs had increased capital training significantly, large firms' capital training in ICT was still, on average, double that of SMEs by 2014. The right panel of Figure 2B.3 shows the distribution by industries. It reveals that capital training in ICT has increased quite steeply across all the industries. Transport equipment is the industry with the largest value, followed closely by agricultural and industrial machinery. The textile, leather and shoes industry remains far behind its counterparts in terms of ICT training capital.

Figure 2B.3: ICT training capital by firm size and industry



Source: ESEE survey and own elaboration.

3. The Extent of Automation

To measure the extent of automation in the production process we use data on four indicators that reflect the use of advanced manufacturing technologies: i) robots, ii) computer-aided design (CAD), iii) flexible manufacturing systems, and iv) local area network (LAN) in manufacturing activity. These technologies imply the application of mechanical, electronic and computer-based systems to operate and control production, having the ability to simultaneously standardize and customize production. Effective deployment of such technologies has been regarded as a way to build a sustainable competitive advantage (Koc and Bozdag, 2009). We describe the different technologies more precisely below.

i) Use of Robots

Robots is a categorical variable taking the value 1 if the firm uses robots in its production processes and 0 otherwise. Information is available between 1990 and 2014, but only every 4 years. To obtain an annual estimate by firm, we proceed by extrapolating the original values forward (see Koch *et al.*, 2021).

ii) Use of Computer-Aided Design (CAD)

This is a categorical variable taking the value 1 if the firm uses CAD and 0 otherwise. As in the case of robots, the information is available between 1990 and 2014 every 4 years. We proceed as above, and to obtain an annual estimate by firm, we extrapolate the original values.

iii) Use of Flexible Systems

This variable informs whether the firm combines machine tools controlled by computer, robotic and/or CAD, through a central computer. Hence, this variable takes the value of 1 if the firm uses flexible manufacturing systems through a central computer and 0 otherwise. As the above variables in this category, data is available every four years since 1991 to 2014. Therefore, we proceed by extrapolating the original values to obtain an annual series by firm.

iv) Use of a Local Area Network (LAN)[41] in Manufacturing Activities

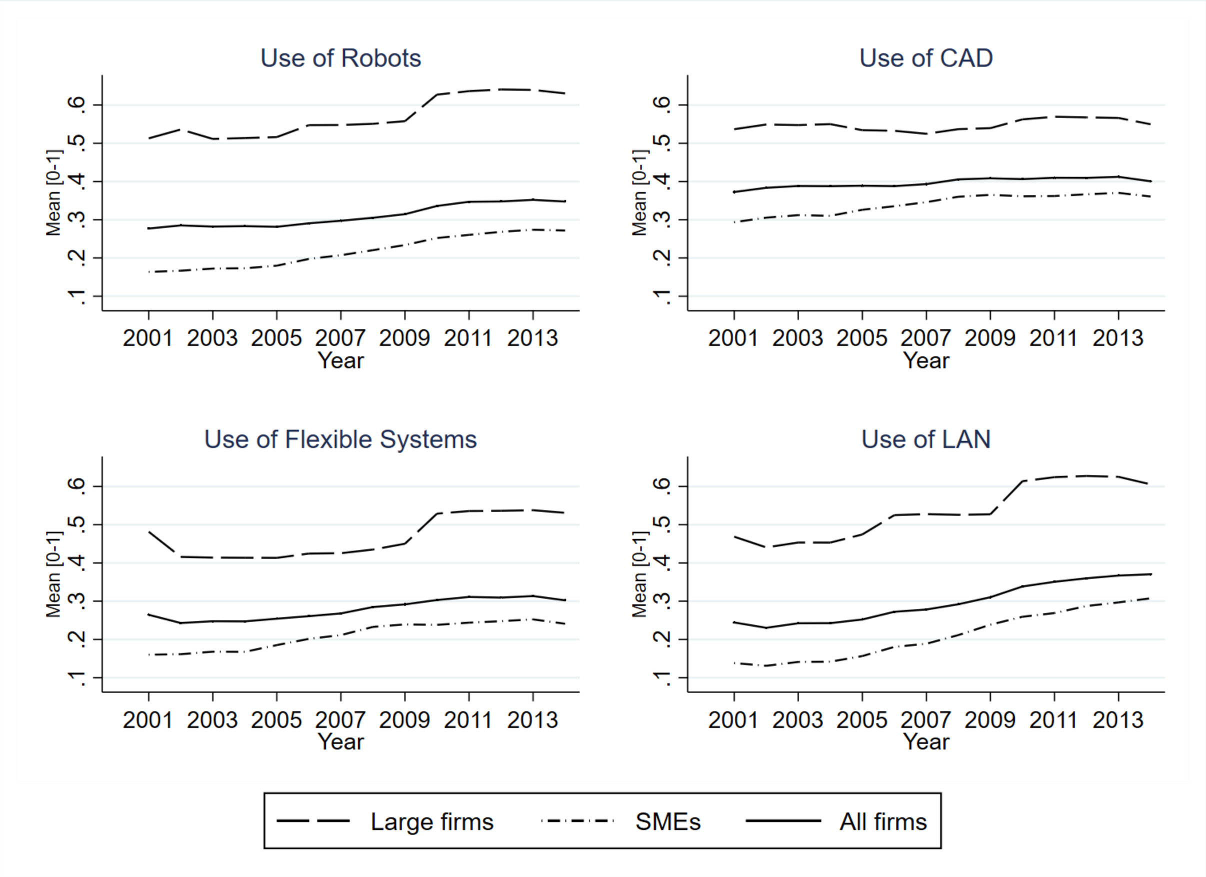
This is also a categorical variable that takes the value of 1 if the firm uses LAN and 0 if it does not. Data is only available since 2000 to 2014 every four years[42]. We extrapolate to obtain an annual series at firm level.

Figure 2B.4 describes the diffusion of automation in Spanish manufacturing firms distinguishing by firm size between 2001 and 2014. Robots use has increased through all the subsamples. Still, large firms appear to use robots around 2.5 times more than SMEs in 2014. More precisely, more than 60% of large firms use robots, whereas less than 30% of SMEs do so. The use of

[41] A local area network is a group of computers and peripheral devices that share common communications line or wireless link to a server within a specific geographical area.
[42] It is also available for the first year in which a firm enters the sample after 2000.

CAD has increased by 7% for SMEs between 2001 and 2014, whereas it has remained quite stable for large firms. Still, the use of CAD appears to be more widespread among large firms, with 55% of them using this technology, than among SMEs, with only 37%. The use of flexible systems has also risen over the millennium, from 17% to around 23% for SMEs, and from 49% to 52% for large firms. Finally, the percentage of SMEs using LAN has more than doubled, from less than 15% to more than 30%. Concerning large firms, it has risen from around 47% to just over 60%.

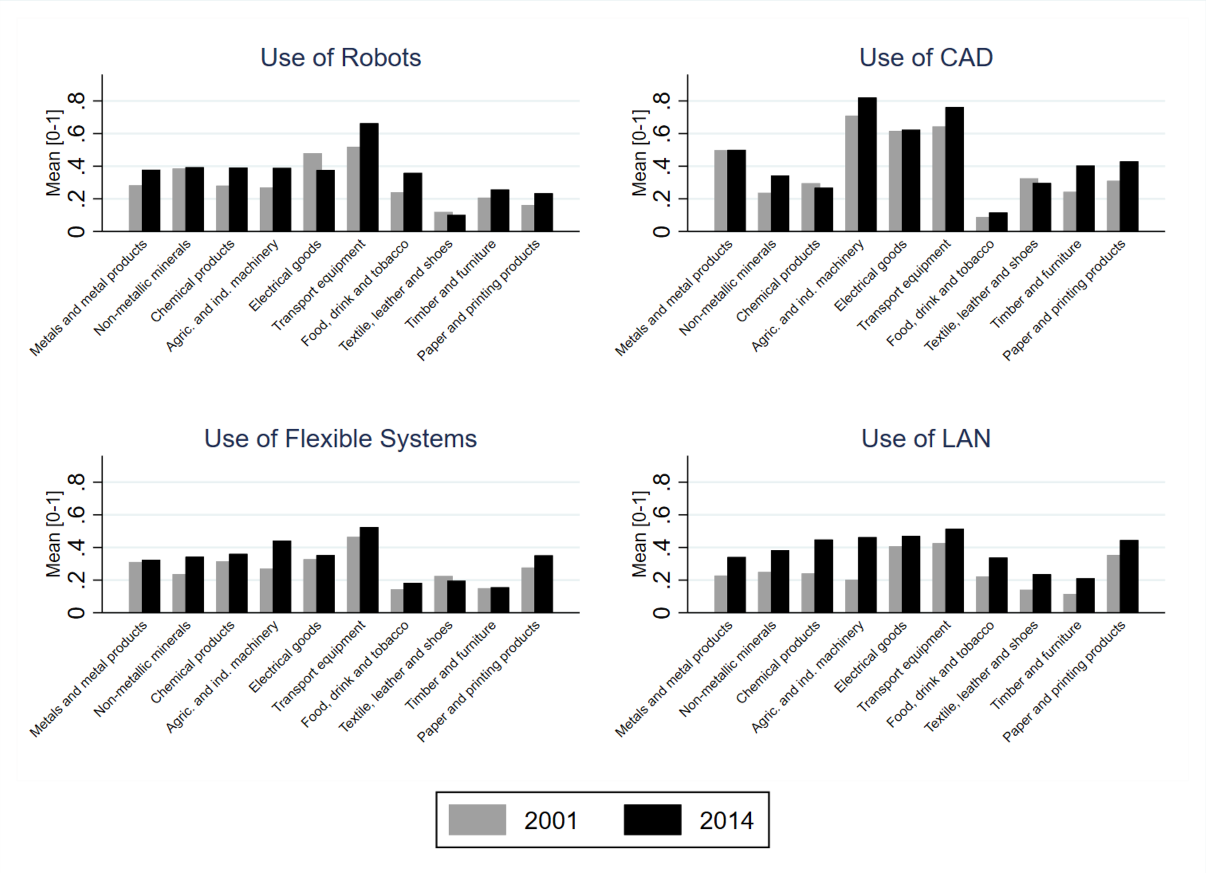
Figure 2B.4: The extent of automation by firm size



Source: ESEE survey and own elaboration.

Figure 2B.5 depicts the average adoption rate of automation by industry over the period 2001-2014. There is substantial heterogeneity across industries in the extent of automation. By 2014, transport equipment is the industry in which, on average, there is a higher percentage of firms using robots (above 60%), flexible systems through a central computer (above 50%), and LAN in manufacturing activities (above 50%). Computer-aided design is the most adopted technology, particularly in the agricultural and industrial machinery industry (above 80%), transport equipment (around 75%) and electrical goods (above 60%). The industries in which automation is less extended are the textile industry (particularly in the use of robots and LAN), the food industry (specifically in the use of CAD), and the furniture industry (mainly in terms of LAN use and flexible systems). These results are in line with the study of Calvino *et al.* (2018).

Figure 2B.5: The extent of automation by industry



Source: ESEE survey and own elaboration.

4. Digital Interaction with Stakeholders

The final dimension reflects the way firms behave on the markets, and more specifically, it looks at how firms use DTs to interact with their stakeholders. Thus, we consider i) the ownership of an internet domain, ii) the existence of a web page stored in the company's servers, iii) the use of online purchases, iv) the use of online sales to companies (B2B), and v) the use of online sales to customers (B2C).

i) Ownership of an Internet Domain

This variable takes the value 1 if the firm has its own internet domain and 0 otherwise. Data is available since 2000 to 2014 on annual basis.

ii) Website Hosted in the Company's Servers

This is a binary variable that takes the value 1 if the firm has a web page in the company's servers and 0 otherwise. Information is given for every year between 2000 and 2014.

iii) Online Purchases

This is a binary variable taking the value 1 if the firm purchases goods or services online and 0 if it does not. Data is available annually between 2000 and 2014.

iv) Online Sales to Companies

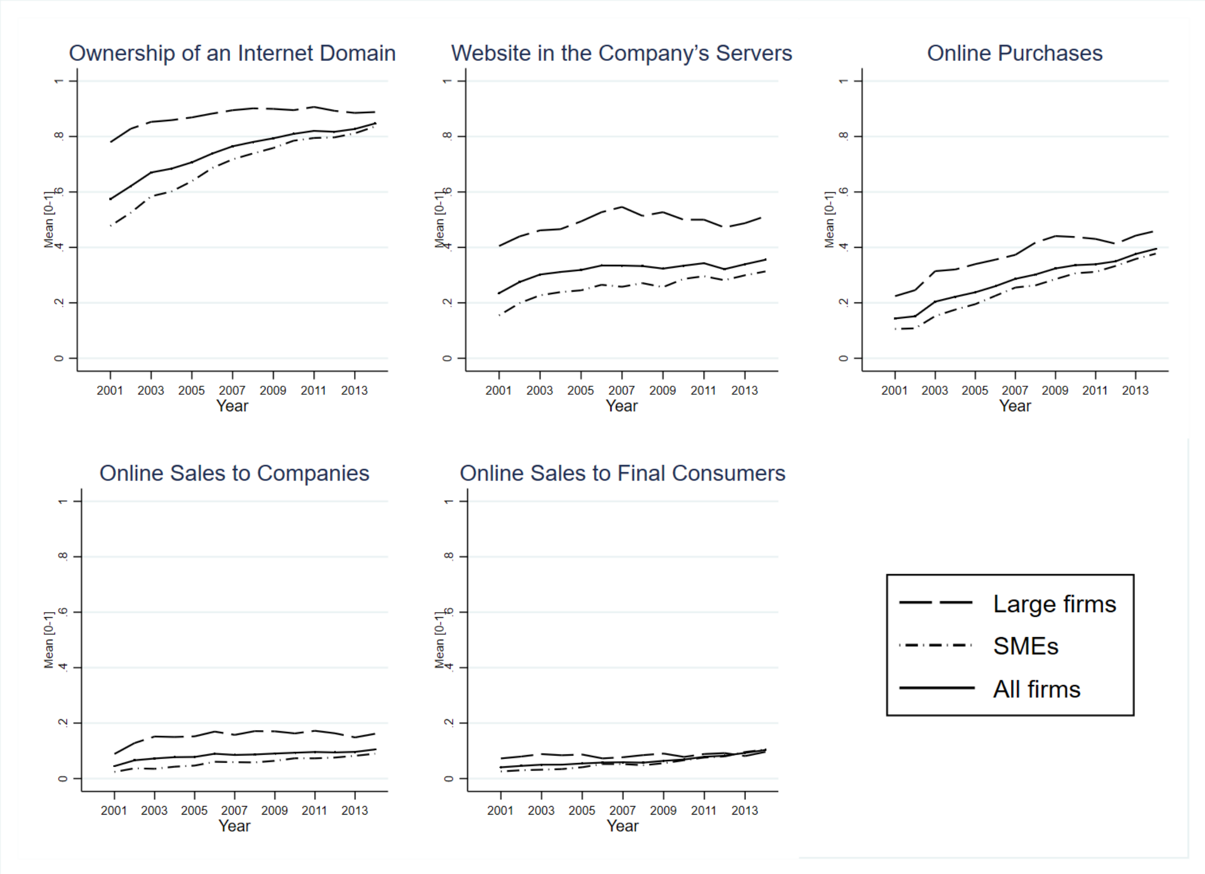
Online sales to other firms (or B2B) is a binary variable that takes the value 1 if the firm sells to companies through internet and 0 otherwise. As for online purchases, information is provided yearly from 2000 to 2014.

v) Online Sales to Final Consumers

This is a categorical variable that captures whether the firm sells to final consumers through internet (or B2C). Information is provided annually from 2000 to 2014.

Figure 2B.6 depicts the extent to which Spanish manufacturing firms have used DTs to interact in the market with their stakeholders over the period of analysis. The proportion of firms owning of an internet domain has risen from less than 60% in 2001 to more than 80% in 2014; firms having a webpage in the company's servers have increased from 25% to 35%; those engaging in online purchases have gone from slightly more than 20% to more than 45%; and firms selling online to other companies or to end consumers have grown from less than 5% to more than 10%. These figures are higher for large firms and lower for SMEs across all the components and for the entire period of analysis, with the exception of online sales to final consumers. In fact, SMEs appear to overtake large firms by 2013 and engage more in this type of activity than their larger counterparts.

Figure 2B.6: The extent of digital contact with stakeholders by firm size



Source: ESEE survey and own elaboration.

Figure 2B.7 depicts the average extent of digital contact with stakeholders by industry between 2001 and 2014. The most widespread technology appears to be the ownership of an internet domain. In 2014, the agricultural and industrial machinery industry is the industry with the highest proportion of companies owning an internet domain (around 95%) and having a website in the company's servers (almost 50%). The electrical goods industry has the highest percentage of firms engaging in online purchases (almost 70%) and sales to other companies (around 17%), whereas the timber, leather and shoes industry leads the way in terms of online sales to final consumers (almost 20%). The industries where the digital contact with stakeholders is the least extended in 2014 are timber, leather and shoes with regard to owning an internet domain, having a website in the company's servers and purchasing online, and non-metallic minerals in terms of selling online to other companies and final consumers.

Figure 2B.7: The extent of digital contact with stakeholders by industry

Source: ESEE survey and own elaboration.

2.B.2. The Synthetic Digitalization Index

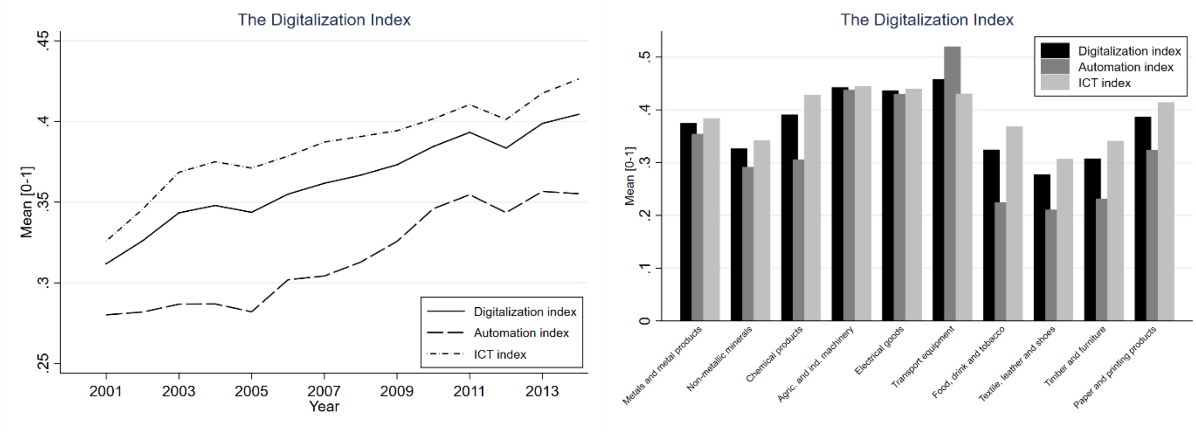
Overall, the digitization index is built from 13 variables grouped in 4 different dimensions of the digital transformation process, in line with Calvino *et al.* (2018). These dimensions, described above, refer to firm's technological components (proxied by ICT capital, computer programming services and the implementation of software programs either hired or developed by the focal firm); the digital-related human capital (proxied by capitalized personnel training in software and information technology); the extent of automation (measured by the use of robots, computer-aided design, flexible systems, and the use of LAN in manufacturing activities); and the way digitalization changes how firms interact with their stakeholders (measured by the ownership of an internet domain, the existence of a webpage stored in the company's server, and the use of different modalities of e-commerce: B2B, B2C, and e-buying). In total, the synthetic index collapses information on 13 components that contain relevant information relative to the digital transformation.

Although the details of the procedure for each component have been described above, the procedure to build the digitalization index can be summarized as follows. First, variables in monetary units (ICT investment and training costs) are capitalized and their relative value with respect to the industry-year mean is classified according to the decile of the distribution to which they belong. The result is then rescaled in the [0-1] range. Categorical variables available only every 4 years (use of robots, CAD, flexible systems and LAN), are first extrapolated and then normalized in the [0-1] interval. The rest of categorical variables are not transformed. As a result, we end up with 13 components ranging from 0 to 1. Finally, to obtain a synthetic index, we combine the information of these components as an unweighted sum. The result is subsequently normalized in the [0-1] interval. Values close to 0 imply that the firm in that particular period is very little digitalized, while values close to 1 suggest a high degree of digitalization in the dimensions considered.

Finally, in order to distinguish the impact of two different types of DTs throughout the thesis, we disentangle the digitalization index into two sub-indices, the ICT index and the automation index. The latter includes the variables presented in the dimension concerning the extent of automation, namely, the use of robots, CAD, flexible systems and LAN. The ICT index includes the remaining dimensions constituting the digitalization index. These indices are also normalized in the [0-1] interval.

The right panel of Figure 2B.8 shows that manufacturing firms in Spain have become more digitalized over time. It is also worth noting that firms lean more towards ICT technologies than automation technologies, as probably the adjustment costs for the latter are considerably higher. Nevertheless, these two types of technologies appear to be increasingly present over the period of analysis. Indeed, both the ICT index and the automation index show a significant increase. This increase is observed at the general level and for the various industries, albeit important differences. Thus, the left panel of Figure 2B.8 shows that the most digitalized industry, i.e., the one with the highest digitalization index, is transport equipment, which is also the industry in which automation technologies are most widespread. As for ICT technologies, the industry making the most use of them seems to be the agricultural and industrial machinery industry. The least digitalized industry is the textile leather and shoes industry, which is also the one in which automation and ICT technologies are least prevalent.

Figure 2B.8: The digitalization, automation and ICT indices



Source: ESEE survey and own elaboration.

Chapter 3

3.1. Introduction

Over the centuries there have been several technological revolutions (Barbieri *et al.*, 2019). The first began in the mid-18th century with the steam engine, and it was followed by electricity two centuries later, and the ICT revolution at the end of the last century. We are currently in the incipient stages of a new – the fourth – industrial revolution, led by the diffusion of robots and artificial intelligence (AI). The main difference between the current revolution and its predecessors is that the technologies involved are capable of performing tasks that require human intelligence and physical ability, and thus have the potential to be more disruptive than their predecessors. In this regard, Bessen (2019) estimates that between 9% and 47% of jobs in this new technological revolution are threatened by automation. According to Arntz *et al.* (2016), 12% of the jobs in Spain are automatable. This figure is higher than the OECD average (9%). This raises an important question: will machines eventually replace humans in their jobs? and if so, to what extent? In this study, we aim to provide evidence for Spanish manufacturing firms in order to answer this question. Furthermore, we aim to analyze the impact of DTs on different types of workers.

Daron Acemoglu testified at a hearing to the US House of Representatives in November 2021 that before the mid-1980s, automation boosted workers' productivity and created new opportunities for them. Since then, automation has accelerated while the creation of new tasks has suffered a strong deceleration, resulting in a net loss of jobs and a negative impact of automation on total employment[43]. In contrast, the Asian Development Bank suggests that robots could promote jobs rather than destroy them. Increased demand, driven by increased efficiency and higher labor productivity, more than offsets the replacement of jobs caused by digitalization[44]. However, concerns have arisen following recent articles suggesting that the COVID-19 pandemic has accelerated the automation of jobs, especially the

[43] https://www.ft.com/content/59321a73-5f88-4e94-9aa2-62e4927783b1
[44] https://www.ft.com/content/69602a90-3d4a-11e8-b9f9-de94fa33a81e

jobs involving non-manual routine tasks[45]. Nevertheless, the fact that there are about 30 million job vacancies in OECD countries tends to contradict this theory. Furthermore, evidence of employment shrinking is very scarce, and this even for routine jobs relative to other sorts of jobs[46]. Concerning the situation in Spain, the same concern is observed. The recent pandemic has accelerated the automation of jobs and, although the creation of new jobs may compensate for the loss of certain jobs, it is argued that those who lose their jobs are not prepared or trained for the new jobs[47].

This general debate reflects the lack of consensus among studies in this area of research, with some scholars arguing that as a result of automation and digitalization employment will increase (see, for instance, Gregory *et al.*, 2016; Aghion *et al.*, 2020), others argue that it will shrink (for example, Chiacchio *et al.*, 2018; Acemoglu and Restrepo, 2020) , and still others claims that it will depend on the level of routineness or skill, industry, or occupation (see, e.g., Gaggl and Wright, 2017; Akerman *et al.*, 2015; Cirillo *et al.*, 2021).

Moreover, depending on the type of worker, digitalization can have a different impact. There appears to be agreement that digitalization benefits high-skilled employment, whereas the impact on low-skilled employment is more uncertain. Some scholars argue for a positive effect (Dutz *et al.*, 2018, Aghion *et al.*, 2020), while some provide evidence of a negative effect (see, for instance, Akerman *et al.*, 2015; Humlum, 2019). A number of studies suggests a negative association with digitalization for manufacturing jobs (Dauth *et al.*, 2017; Mann and Püttman, 2017; Dottori, 2021) or no effect at all (Gaggl and Wright, 2017). Nevertheless, evidence on temporary and permanent contract workers is very scarce (Doménech *et al.*, 2018), so assessing the potential impact on both types of workers is worthwhile, given that the cost of dismissal of temporary workers is much lower. This analysis may be of interest for countries such as Spain, where the share of workers with temporary contracts is relatively higher compared to other European countries[48].

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[45]https://www.theguardian.com/business/2020/dec/15/more-than-half-of-uk-furloughed-jobs-at-risk-of-automation-report
[46]https://www.economist.com/finance-and-economics/2022/01/22/economists-are-revising-their-views-on-robots-and-jobs
[47]https://www.eldiario.es/opinion/zona-critica/covid-acelerador-mayor-impulso-automatizacion_129_7248443.html
[48]https://ec.europa.eu/eurostat/web/products-eurostat-news/-/DDN-201905241#:~:text=In%202018%2C%20temporary%20employees%20aged,the%20European%20Union%20(EU)

Most studies analyzing the employment impact of DTs use single indicators for the digitalization phenomenon, which are only able to partially capture the degree of penetration of (certain) DTs and struggle to reflect the rapid pace at which digital transformation has developed. In doing so, they ignore the fact that digitalization is a complex phenomenon that is poorly captured by a single indicator. To overcome these drawbacks, and in line with Chapter 2, we follow Calvino *et al.* (2018) and construct a synthetic index of digitalization at the firm level that accounts for the multi-faceted phenomenon of the digital transformation.

The ultimate aim of this study is to analyze the relationship between the digital transformation in Spanish manufacturing firms and its impact on manufacturing employment. To do so, we follow Ortiz and Salas Fumás (2020), and estimate a demand for labor by profit-maximizing firms. Moreover, we assume an endogenous Markov process in which the digitalization index is allowed to impact firms' future productivity, allowing us to empirically assess not only the direct impact of digitalization on employment, but also an impact through TFP, referred as the productivity effect. The direct impact will combine two effects induced by the use of DTs. On the one hand, the demand-scale effect, as these technologies allow firms to access a wider market as seen in Chapters 1 and 2, and on the other hand, the potential replacement (or substitution) effect of these technologies.

We will also distinguish the role of automation from other DTs, referred to collectively as ICTs. To do so, we use two distinct indices to capture these two different components of digitalization. The first component is the ICT index, which covers the technological components, digital-related human capital, and how firms use DTs to interact with stakeholders. The ICT index is expected not only to increase productivity, but also to act as complement to workers and thus increase employment beyond the demand-scale effect. In contrast, the impact of automation may be more uncertain, since, for example, robots are thought to boost productivity but also replace workers in certain tasks. In this case, employment would increase if the productivity effect dominates the displacement effect. However, as mentioned in the previous chapter while ICTs may lead to the fragmentation of value chains and the outsourcing of labor-intensive task, thus reducing employment, automation is likely to induce "reshoring" of some tasks previously outsourced, therefore leading to more employment at home.

Our results suggest that digitalization has a positive and significant direct impact on firms' employment, as the demand-scale effect outweighs the potential replacement effect, and there is also a positive productivity effect. Furthermore, SMEs' employment is positively related to digitalization, through both the direct and productivity effect, whereas no statistically significant direct effect is detected for larger firms. Digitalization also has a positive effect on the number of different categories of worker. However, when we analyze the impact of digitalization on the composition of employment, we find that digitalization has a positive impact on the share of skilled workers but a negative effect on the share of unskilled workers. There is both a negative direct and productivity effect on the share of unskilled workers, and on the share of manufacturing workers. In contrast, we find no direct effect of digitalization on the proportion of temporary contract workers, who still benefit from a productivity effect.

The rest of the chapter is structured as follows. First, we review the existent literature analyzing the impact of new technologies on employment. We then describe the methodology before introducing the data and some descriptive statistics. Finally, we present the empirical results and discuss the findings, implications, and limitations of this study.

3.2. Literature Review

New technologies based on digitalization and automation can either be labor saving in some tasks and productivity-enhancing in other tasks, leading to lower prices and higher demand (Dottori, 2021), and potentially create new jobs in non-automated tasks (Autor, 2015), as well as create new tasks (Acemoglu and Restrepo, 2019). Dosi *et al.* (2021) even argue that the demand enhancing effect can extend to other markets for both goods and services. As a result, DTs can either act as a substitute for labor (referred to as a displacement effect), reducing employment, or, on the contrary, as complementary, increasing employment (Zator, 2019). Indeed, digitalization and automation enable to allocate tasks to factors in a more flexible manner, resulting in higher value added and, as a result, an increase in labor demand for non-automated tasks and an increase in overall employment (Acemoglu and Restrepo, 2019). However, automation has also the potential to reduce the labor share, as machines replace workers in some tasks.

The question is whether the net new jobs created by new technologies and their productivity effect can offset the displacement effect and the jobs that have been replaced by machines and robots. Depending on a plethora of factors, such as the industry or the skills of the workers, one effect may be stronger than the other and thus alter the net effect on employment. For example, it is argued that robots are more likely to perform routine tasks than tasks requiring higher skills, resulting in a loss of employment in routine tasks performed by medium-skilled workers. Hence, the literature suggests that there is a certain job polarization, by which high-skilled workers stand to gain the most from the digital transformation, followed by low-skilled workers, who will still benefit, but less. In contrast, medium-skilled workers stand to lose the most (Michaels *et al.*, 2014).

Nevertheless, most studies seem to agree that digitalization has a net positive impact on employment. According to the survey conducted by Barbieri *et al.* (2019), the impact of digitalization at the micro level is generally positive for employment, implying the creation of new jobs as a result of the ICT revolution. However, the results are quite different when disaggregated by skills. While there seems to be a positive relationship between skilled workers and new technologies, the relationship weaker or even non-existent when low-skilled or particularly, medium-skilled workers are considered. The survey also seems to concur that middle-skilled occupations may suffer more from technology adoption than other occupations. This implies that if we classify occupations by wages, the upper end of the distribution, i.e., professional occupations, would grow, the lower end of the distribution, i.e., elementary occupations, would grow but to a lesser extent, and the middle of the distribution, i.e., machine or electronic equipment operators, for example, would suffer a decline in employment. This polarization may be due to the fact that not only the dimensions of education and occupations are relevant in the analysis, but also the dimension of routine and how easily a particular task could be performed by a machine or robot.

The empirical literature on the impact of digitalization on labor market outcomes can be divided into three strands, depending on the level of analysis. First, studies using local labor markets and regional data, then industry-level data, and finally firm-level data. Table 3A.1 in appendix 3.A shows a summary of the key findings of these studies.

At the level of analysis of the local labor markets, Gregory *et al.* (2016) find that routine-replacing technological change has increased labor demand by up to 11.6 million jobs in Europe. Dauth *et al.* (2017) suggest that job losses from the use of robots in the manufacturing sector are offset by job creation in the service sector, suggesting reallocation rather than elimination. Mann and Püttmann (2017) confirm this intuition, confirming a decline in manufacturing jobs caused by automation and offset by the expansion of employment in the service sectors. However, Chiacchio *et al.* (2018) reach a different conclusion, finding a negative impact of robots on employment rates, especially for workers with intermediate education levels, i.e., with at least upper secondary education, but no impact on wages. Similarly, Acemoglu and Restrepo (2020) find a negative effect of robotization on both employment and wages. More specifically, one additional robot per 1000 workers would reduce employment by 3.3 workers and annual wages by $200. In contrast, Dottori (2021) points out that the introduction of robots may benefit to greater extent blue-collar workers rather than white-collar workers, while this effect is reversed for wages. In addition to these results, Dottori (2021) cannot identify any negative impact of robotization on employment at the local labor market level, except for a very weak negative effect in manufacturing, estimating that exposure to robots could account for about 1/6 of the employment decline in these industries.

In terms of industry-level data, Michaels *et al.* (2014) evidence that ICT growth is associated with a significant increase in the demand for highly-skilled workers relative to medium-skilled workers as well as a significant, but smaller, increase in demand for low-skilled workers relative to medium-skilled workers. Similarly, Falk and Biagi (2017) find a positive relationship between the share of workers with a university degree and several ICT applications, such as enterprise resource planning, automatic data exchange, and electronic invoicing. Moreover, the share of the skilled workforce is also positively associated with the share of broadband-enabled workers and workers with mobile internet access. However, ICT appears to have a negligible impact on unskilled workers, but a strong and negative effect on the relative demand for workers with an intermediate education. Graetz and Michaels (2018) find no effect of robotization on total employment, and only a negative effect for low-skilled workers. They also identify a positive and significant effect on wages. According to Klenert *et al.* (2020), there is a positive correlation between robots and total employment. Moreover, they find no evidence that robots are reducing the share of low-skilled workers in Europe.

In studies using firm-level data, Gaggl and Wright (2017) find that ICT increases employment in the wholesale trade, retail trade, and financial sectors, but has no effect on manufacturing. This effect also appears to differ between firms within the same industry. Akerman *et al.* (2015) point to a positive and significant effect of Internet technologies on the employment of skilled workers, whereas the effect is negative for unskilled workers. They point to a complementarity effect between the adoption of broadband technologies and skilled workers in non-routine tasks and a substitution effect between unskilled workers and routine tasks. Dutz *et al.* (2018) point out that the adoption of ICT at the firm level in Argentina, Chile, Colombia, and Mexico is associated with an increase in total employment, even among low-skilled workers. This can be explained by the fact that the productivity effect outweighs the substitution effect, and thus the replacement of low-skilled jobs by technologies or by high-skilled jobs is overcome by the increase in total employment of low-skilled workers. Dixon *et al.* (2019) suggest that investment in robotics is associated with an increase in total employment within the firm. However, companies that employ many low-skilled workers suffer more from the consequences of the substitution effect caused by digitalization (Zator, 2019). In this line, Humlum (2019) evidences that robot adopters shift from low-skilled to high-skilled labor. Babina *et al.* (2020) find that firms investing more in artificial intelligence experience faster growth in employment. Aghion *et al.* (2020) also find a positive effect of automation technologies on overall employment and low-skilled employment. More recently, Cirillo *et al.* (2021) suggest that digitalization has a small positive and significant effect on employment, implying that employment tends to increase in highly digitalized jobs. However, when digitalization is paired with routineness, the effect on employment becomes negative. This means that there could be a substitution effect of technology on employment for tasks that are highly digitalized but also highly routinized. In this context, they use the Routine Task Intensity index (RTI), index which classifies tasks into three main categories, routine tasks, non-routine cognitive tasks and non-routine manual tasks.

Overall, most of these studies suggest a positive impact of DTs, including robots, on firms' demand for labor (Cusolito *et al.*, 2020), and instead of eliminating jobs, they would be reallocated from one industry to another (Bessen, 2019). Overall, however, it seems complicated to assess any trend with respect to the existing literature. Indeed, the impact of digitalization on employment is ambiguous, sometimes positive, sometimes negative, and even non-existent. However, most studies seem to agree that the impact on manufacturing employment is negative, implying a decrease in the demand for labor by manufacturing firms and a loss of jobs in these sectors. Nevertheless, the recent results for Spain, based on the ESEE dataset are not entirely clear. Camiña *et al.* (2020) suggest a negative effect of automation technologies on employment in Spanish manufacturing firms. This effect is slightly weakened, but still negative, when considering only the 2000-2016 period. Automation has a positive effect on long-term employment only when paired with human capital. In contrast, Stapleton and Webb (2020) demonstrate a positive effect, although weak, of the introduction of robots on employment. However, this effect is not robust for all specifications. They also find that robot adoption doubles the number of engineers and college graduates and increases production employment by 80%, while it has no effect on college graduates and administrative workers. Finally, Koch *et al.* (2021) show that Spanish manufacturing firms that adopt robots increase employment compared to a non-adopter firm belonging to the same industry, implying that we assist to a reallocation of productivity and employment in favor of robot adopters. Those who adopt robots can expect their employment to increase by about 10%. Moreover, there is no negative impact of robotization for low-skilled workers, i.e., workers who do not have a 5-year college degree.

Our contribution to the literature is manyfold. Most of the studies listed in this review use indicators that capture only one phenomenon of the digital transformation, such as robotization or automation, or use only ICT applications, whereas we include 13 components of the digital transformation into a synthetic index to better capture the degree of digitalization. Second, we analyze both the direct effect of digitalization on employment and the productivity effect using a model that considers profit-maximizing firms and allows for imperfect competition in product markets (Ortiz and Salas Fumás, 2020). Under profit-maximization the labor demand depends on product demand factors, such as market power, that are not relevant under cost-minimization, which is the standard approach. Finally, we explore the impact of digitalization in different types of employment.

3.3. Methodology

To examine the effects of digitalization on firm's labor demand, we adopt a model of a profit-maximizing firm (see Milner and Wright, 1998; Ortiz and Salas Fumás, 2020). We follow Ortiz and Salas Fumás (2020) and assume that the firm's output demand function is $Q = Dp^{-\varepsilon}$, where Q is the quantity demanded at unit price *p*, *D* is a parameter directly depending on digitalization, which enlarges the potential size of the market at this price. As seen from previous chapters, DTs enable firms to reach more customers and thus to expand their market size. The parameter ε is the (assumed) constant price elasticity of demand. From this, we obtain the inverse demand function $p = D^{1/\varepsilon}Q^{-1/\varepsilon}$. Therefore, total revenue is given as $R = pQ = BQ^{\mu}$, where $B = D^{1/\varepsilon}$ and $\mu = \frac{\varepsilon-1}{\varepsilon}$. These parameters allow us to consider an imperfectly competitive product market. This contrasts with previous literature assuming a perfectly competitive product market, where $\varepsilon = \infty$ and $\mu = 1$ (Van Reenen, 1997).

As in previous chapters, we consider a Cobb-Douglas production function:

$$Q_{it} = A_{it}K_{it}^{\alpha}L_{it}^{\beta}M_{it}^{\gamma} \tag{3.1}$$

where *K* is capital, *L* is labor, and *M* is intermediate inputs. α, β, and γ are output elasticities parameters with respect to each input that take values between 0 and 1. The sum of the three output elasticities is equal to δ. If δ is greater than 0, there are increasing returns to scale, if it is lower than zero, decreasing returns to scale, and if it is equal to zero, constant returns to scale. We assume that *A* the parameter representing the technical efficiency of the production process can be modelled as $A=exp(\omega_{it}, e_{it})$, where ω_{it} is the firm's TFP, which is assumed to be observable by the firm but not by the analyst; and e_{it} is the error term. Moreover, we assume that digitalization enables firms to source inputs more efficiently as well as to innovate (Tambe and Hitt, 2014). Hence, accounting for the potential role of digitalization in enhancing TFP, implies modelling productivity as a first order endogenous Markov process that depends on the firm's degree of digitalization and a random shock, such that:

$$\omega_{it} = g(\omega_{it-1}, DIG_{it-1}) + \xi_{it} \tag{3.2}$$

where g(.) is an unknown function, and $\xi_{it}$is an unexpected innovation shock. The problem of profit-maximization of the firm can be formulated as follows:

$$Max_{K,L,M}\pi_{it} = BQ_{it}^{\mu} - rK_{it} - wL_{it} - cM_{it} \tag{3.3}$$
$$s.t.: Q_{it} = AK_{it}^{\alpha}L_{it}^{\beta}M_{it}^{\gamma}$$

where *r*, *w* and *c* represent the cost of capital, labor and intermediate inputs, respectively. From the profit maximization problem (see, Ortiz and Salas Fumás, 2020), we can derive the first order condition for labor:

$$\frac{\partial\pi_{it}}{\partial L_{it}} = \frac{B\mu\beta\left(AK_{it}^{\alpha}L_{it}^{\beta}M_{it}^{\gamma}\right)^{\mu}}{L_{it}} - w = 0 \tag{3.4}$$

Similarly, we obtain the optimal solutions for capital and intermediate inputs, and substitute these solutions into equation (3.4). Moreover, taking logs, and given that $B = D^{1/\varepsilon}$ and $\alpha + \beta + \gamma = \delta$, we can rearrange to obtain the reduced form of the labor demand[49]:

$$lnL_{it} = \frac{1-\mu}{1-\mu\delta}lnD + \frac{1}{1-\mu\delta}ln\mu + \frac{\mu}{1-\mu\delta}lnA + \frac{1-\mu(\alpha+\gamma)}{1-\mu\delta}ln\left(\frac{\beta}{w}\right) + \frac{\alpha\mu}{1-\mu\delta}ln\left(\frac{\alpha}{r}\right) + \frac{\gamma\mu}{1-\mu\delta}ln\left(\frac{\gamma}{c}\right) + u_{it} \tag{3.5}$$

where u_{it} is the error term. Moreover, *w* is the cost of labor, which enters as a denominator in the equation, meaning that the higher the real wages, the lower the demand for labor.

Digitalization affects the labor demand in equation (3.5) through three components. The first is through the demand-*scale* effect. As previously stated, *D* is a parameter of the size of the potential market for a given price, which depends directly on digitalization, $D = f(DIG)$. An increase in

[49] More details about how the labor demand is obtained can be found in the appendix 3.B. A meaningful economic solution requires 1 < ε <infinite (0< $\mu \leq 1$) and 0< $\delta\mu < 1$ (Ortiz and Salas Fumás, 2020).

digitalization that raises D will increase the demand for labor (except in price-taking firms, where $\mu = 1$). The second is the *productivity* effect, which is assumed to have a positive impact on the demand for labor. Given that we assume $A=exp(\omega_{it}, e_{it})$, and as shown in equation (3.2), digitalization is allowed to impact on productivity through an endogenous Markov process $\omega_{it} = g(\omega_{it-1}, DIG_{it-1}) + \xi_{it}$. Finally, the *complementarity or substitution* effect of digitalization can be captured through the effect of the price of digital capital, which is contained in the user cost of capital (*r*), on the labor demand. However, we have no information on the user cost of capital, nor on the prices of specific capital assets (i.e., the price of robots, price of computers, etc.). Instead, we use the capital stock (*K*) and the digitalization index (*DIG*). This is consistent with the assumption that (digital) capital is a quasi-fixed input in the short-term[50] (Berman *et al.*, 1994), and in line with the empirical literature examining employment effects of technological change (Van Reenen, 1997; Pantea *et al.*, 2017; Goaied and Sassi, 2019). Additionally, using the capital stock instead of the user cost of capital, allows us to avoid possible problems related to the measurement of the price of capital, for which there is no reliable data at firm level.

For the empirical analysis, we rearrange terms and estimate the following linear specification:

$$l_{it} = \theta_1 DIG_{it} + \lambda_1 \omega_{it-1} + \alpha_1 w_{it-1} + \beta_1 k_{it-1} + \gamma_1 c_{it-1} + \zeta_1 \mu_{it-1} + \sigma_1 X_{it-1} + d_t + d_j + \varepsilon_{it} \quad (3.6)$$

where labor depends on the parameter θ_1, which combines both the demand-scale effect and the potential supply-replacement effect of the digital transformation (DIG_{it-1}). A priori, the sign of this coefficient will depend on whether the positive scale effect dominates or not the negative potential replacement effect. Labor demand also depends positively on the productivity effect of digitalization (ω_{it-1}) and negatively on real average wages (w_{it-1}). It does depend also on the capital stock[51] (k_{it-1}), and on the price of intermediate inputs (c_{it-1}), with the direction of these effects depending on the complementarity or substitutability between these inputs and labor. Finally, it will be determined by the extent of market

[50] Assuming that capital is quasi-fixed in the short term implies that, for yearly variations, even if the cost of capital changes in a significant way, firms will have difficulties to adjust its stock of capital in the short term (Pantea *et al.*, 2017).
[51] Lower capital letters refer to variables in logs.

power of the firm, (μ_{it-1}). Similar to previous studies on the employment effect of technological change, we control for a set of lagged control variables (R&D propensity and export propensity) included in the vector X_{it-1}. d_t and d_j are a set of time and industry effects respectively, and ε_{it} is the idiosyncratic error term accounting for the effect of other time- and firm-specific unobservable determinants.

3.3.1. The Impact of Digitalization on the Workforce Composition

To examine the impact of digitalization on the workforce composition, we use shares of workers categories as a dependent variable, under the same specification as in equation (3.6):

$$s_{it}^{EMP} = \theta_2 DIG_{it} + \lambda_2 \omega_{it-1} + \alpha_2 w_{it-1} + \beta_2 k_{it-1} + \gamma_2 c_{it-1} + \zeta_2 \mu_{it-1} + \sigma_2 X_{it-1} + d_t + d_j + r_{it} + \varepsilon_{it} \tag{3.7}$$

where the dependent variable s_{it}^{EMP} represents the following shares: i) unskilled employment, ii) skilled employment, iii) manufacturing employment, iv) permanent workers, and v) temporary workers. The expected impact of digitalization on each is discussed in greater detail below.

The first employment share we consider is the share of unskilled workers on total employment, which is expected to be negatively related with the digitalization index. This is because unskilled labor is more likely to perform routine tasks, thus it may be more easily replaced by DTs, in particular by robots. In contrast, robots and other DTs may act as a complement to skilled employment. In the case of the share of unskilled employment, the replacement effect is expected to outweigh the scale effect, while the opposite is true for skilled employment. This implies that we expect the coefficient θ_2 to be negative for the unskilled employment share. Hence, the share of unskilled workers is expected to decrease with the increase of digitalization (Graetz and Michaels, 2018) through the parameter θ_2, but still, we expect to find a positive productivity effect through λ_2. Indeed, Autor and Salomons (2017) suggest that productivity growth has contributed to job polarization, implying an increase in skilled and unskilled labor demand at the expense of middle-skilled workers. The same logic can be applied to the analysis of the share of manufacturing workers. According to Dottori (2021), robots could account for about 1/6 of the employment decrease in manufacturing industries. The direct effect of digitalization on the share of temporary workers is more uncertain, and we find no evidence from the existing literature. However, we hypothesize that temporary workers are more likely to be unskilled and much easier to be replaced due to the lower cost of firing compared to permanent workers. Thus, we expect that digitalization will have a negative direct impact on the share of temporary workers, while having a positive impact on the share of permanent workers.

3.3.2. Estimation Methods

To estimate the parameter θ, which informs about the direct impact of digitalization on firms' employment, we must account for the potential endogeneity of the digitalization index. In order to do so, we use two different procedures for equations (3.6) and (3.7) due to the nature of the dependent variable (i.e., a continuous variable versus a share).

The instrumental variable (IV) approach to estimate equation (3.6) is based on a two-stage least-squares (2SLS) estimation procedure. We first instrument the digitalization index with its second lag, which we assume is correlated with the digitalization index but not with the error term. As we stated in Chapter 2, it is common to use lagged variable as instruments in the literature (e.g., Cameron *et al.*, 2005). In the first stage, we regress the digitalization index on its second lag and the rest of the control variables using a fixed effect (FE) specification. In the second stage, the model-estimated values from the first stage are then used instead of the original values of the digitalization index to estimate a FE-OLS model and thus avoid any simultaneity issues.

The dependent variable in equation (3.7) is instead the share of different categories of workers on total employment. This implies that the values of the dependent variable are bounded between 0 and 1. Therefore, a linear regression model like OLS is not appropriate (Kölling, 2020). Instead, we use a fractional response model for panel data (Papke and Wooldridge, 2008; Wooldridge, 2010). In addition, to control for the potential endogeneity of the digitalization index in equation (3.7), we follow Kölling (2020) and apply a control function (CF) approach and treat it as an omitted variable problem (Wooldridge, 2015). As explained in the preceding chapters, the CF consists of two steps. On the first step, we regress the digitalization index on the second lag of the digitalization index and the covariates of the empirical model in a FE model. On the second step, the residual of the first step regression, *residual*$_{it}$, is used as an additional covariate in equation (3.7) to account for the factors that may cause correlation between the digitalization index and the error term. Our identification strategy lies in the fact that the extent of digitalization two periods ago does not influence the current firms' decisions on employment and its components, except through digitalization.

As a robustness check, instead of using the second lag of the digitalization index, we build a new instrument as in Chapter 2. This consists of the mean of the digitalization index by industry, region, size, year, R&D propensity and export status, but excluding the focal firm. Knowing that the firm in question is excluded, we assume that the instrument is exogenous to the firm's labor demand. We then proceed estimating the model with a 2SLS model, as explained above.

3.3.3. TFP Methodology

To estimate the productivity effect of digitalization on employment in equations (3.6) and (3.7), we first estimate a production function. Thus, for each two-digit industry, we estimate firm level TFP with the following Cobb-Douglas production function[52]:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + \omega_{it} + e_{it} \tag{3.8}$$

where y_{it}, l_{it}, k_{it}^{NIT}, k_{it}^{IT}, and m_{it} stand for the logarithms of real gross output, labor, non-ICT capital, ICT capital and materials, respectively. ICT and non-ICT capital are considered as fixed inputs whereas labor and materials are regarded are freely variable. Finally, ω_{it} is the firm's productivity, which we cannot observe but it is assumed that the firm can, and e_{it} is the error term[53].

To estimate the production function, we specify a Markov process for productivity, in which productivity at time $t+1$ depends on the productivity a firm can expect given its information set at time t and on the innovation term ξ_{it+1}, which it is assumed uncorrelated with the state variables. We follow

[52] Here, unlike in Chapter 2, we do not restrict the sample to SMEs, and consider all firms.
[53] The estimated errors are robust to heteroscedasticity and autocorrelation.

Doraszelski and Jaumandreu (2013) and assume an endogenous (first-order) Markov process, in which the digitalization index is also allowed to impact firm's future productivity[54]:

$$\omega_{it+1} = g(\omega_{it}, DIG_{it}) + \xi_{it+1} \tag{3.9}$$

Using OLS to estimate equation (3.8) yields biased and inconsistent estimates due to the fact the firm chooses its inputs, especially the freely variable inputs, depending on firms' productivity ω_{it}. As in previous chapters, we address this problem by using a control function approach following (see Olley and Pakes, 1996; Levinsohn and Petrin, 2003) which will allow us to estimate equation (3.8) consistently. More precisely, we follow Wooldridge (2009)[55] and use a GMM estimation. In doing so, we assume that the demand for materials is a function of the state variables and productivity, and under certain conditions it can be inverted. Hence, we obtain: $\omega_{it} = m_t^{-1}\left(k_{it}^{IT}, k_{it}^{NIT}, m_{it}\right) = h_t\left(k_{it}^{IT}, k_{it}^{NIT}, m_{it}\right)$. Finally, substituting this expression into equation (3.8) leads to the first equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + h_t\left(k_{it}^{IT}, k_{it}^{NIT}, m_{it}\right) + e_{it} \tag{3.10}$$

However, from equation (3.10), we cannot identify the coefficients of both capitals and materials since h_t is an unknown function[56]. Therefore, to identify these coefficients, we need an additional equation that deals with the law of motion of productivity (Wooldridge, 2009), Hence, we assume that productivity depends on the endogenous Markov process as in equation (3.9). Knowing that $\omega_{it} = h_t\left(k_{it}^{IT},\ k_{it}^{NIT},\ m_{it}\right)$, equation (3.9) becomes $\omega_{it} = f\left(h_t\left(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}\right), DIG_{it-1}\right) + \xi_{it} =$

[54] We could model the endogenous Markov process as a function of trade status as we did in Chapter 2. However, for clarity here we only assume that TFP depends endogenously of the digitalization index.

[55] The method distinguishes between state variables, in our case both types of capital, and flexible variables, here labor and materials. The realization of the state variables in period *t* is decided based on the information in *t-1*, and thus they are not affected by the productivity shock arriving t, while flexible variables are determined in response to the shock.

[56] We proxy *h*(.) by a third-degree polynomial in its arguments.

$g_t\left(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DIG_{it-1}\right) + \xi_{it}$; and then plug it into equation (3.8) to obtain the second equation we will estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + g_t\left(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DIG_{it-1}\right) + u_{it} \tag{3.11}$$

where we proxy $g_t(.)$ with a third-degree polynomial in its arguments. The composed error term is $u_{it} = \xi_{it} + e_{it}$.

Table 3.1: Results of the estimation of the production function

Industry	l	k^{NIT}	k^{IT}	m	Observations
1. Metals and metal products	0.200***	0.048***	0.010***	0.733***	2,486
	(0.008)	(0.008)	(0.003)	(0.011)	
2. Non-metallic minerals	0.230***	0.090***	0.009*	0.660***	1,133
	(0.011)	(0.013)	(0.005)	(0.021)	
3. Chemical products	0.199***	0.062***	0.017***	0.694***	2,010
	(0.009)	(0.009)	(0.003)	(0.022)	
4. Agric. and ind. machinery	0.205***	0.045***	0.017***	0.695***	1,029
	(0.012)	(0.015)	(0.005)	(0.023)	
5. Electrical goods	0.207***	0.056***	0.043***	0.681***	1,064
	(0.011)	(0.011)	(0.004)	(0.017)	
6. Transport equipment	0.184***	0.062***	0.014***	0.718***	1,232
	(0.011)	(0.012)	(0.005)	(0.017)	
7. Food, drink and tobacco	0.107***	0.090***	0.016***	0.675***	2,468
	(0.007)	(0.008)	(0.003)	(0.024)	
8. Textile, leather and shoes	0.331***	0.086***	0.008*	0.485***	1,419
	(0.014)	(0.018)	(0.004)	(0.043)	
9. Timber and furniture	0.220***	0.033***	0.021***	0.679***	1,309
	(0.010)	(0.009)	(0.004)	(0.020)	
10. Paper and printing products	0.251***	0.082***	0.010***	0.599***	1,330
	(0.011)	(0.009)	(0.003)	(0.023)	

Notes: Estimates of the input coefficients from equation (3.12) are shown for different industries using the GMM estimation proposed by Wooldridge (2009). The dependent variable is the log of gross output. Each row represents a separate regression. Robust standard errors are reported in parenthesis. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

We follow Wooldridge (2009) to estimate equations (3.10) and (3.11) jointly by GMM, using the appropriate set of instruments[57]. This is done for each of the 10 industries considered. Thus, we obtain industry-specific output elasticity estimates and firm-specific TFP estimates. These results are presented

[57] We follow Doraszelski and Jaumandreu (2013) and De Loecker (2013) and do not account for sample selection by modelling a firm's exit decision.

in Table 3.1 and show that the elasticity of the ICT capital is significant across all the 10 industries, being the lowest (0.008 and 0.009) in the textile, leather and shoe industry, and in the non-metallic minerals industry, respectively, and the highest (0.043) in the electrical goods industry. The labor elasticity is the highest in the textile, leather and shoes industry (0.331) and the lowest in the food, drink and tobacco industry (0.107); non-ICT capital elasticity is the highest in the non-metallic minerals and food, drink and tobacco industries (0.090) and the lowest in the timber and furniture industry (0.033); and the intermediate inputs elasticity is the highest in the metals and metal products industry (0.733) and the lowest in the textile, leather and shoes industry (0.485).

In order to have evidence of the productivity effect of digitalization on employment, the digitalization index must have, first, a significant effect on TFP[58] and, second, the TFP's coefficient must be significant in the labor demand equation. To verify the first condition, we consider a linear specification of the Markov process described by equation (3.9):

$$\omega_{it} = \beta_1\omega_{it-1} + \beta_2 DIG_{it-1} + \gamma' z_{it-1} + \alpha_j + \alpha_t + \alpha_i + \epsilon_{it} \tag{3.12}$$

where ω_{it} is firm's TFP that is a function of its lagged value, the lagged digitalization index and other control variables that may influence the evolution of productivity, including a vector of observed firm characteristics (z_{it-1}), sector dummies (α_j), year dummies (α_t), and firm fixed effects (α_i). Positive and significant estimates of β_2 are interpreted as an enhancing effect of digitalization on TFP. Equation (3.12) is estimated by the two-step system-GMM estimator for dynamic models (Arellano and Bover, 1995; Blundell and Bond, 1998), which accounts for unobserved heterogeneity and the endogeneity bias[59]. All the specifications provide suitable results for the Hansen test of overidentifying restrictions[60] (testing for instruments validity) and for the non-serial correlation of the error terms[61]. As shown in

[58] To control for the impact of outliers, we winsorize the resulting distribution of TFP at the 1st and 99th percentile.

[59] Eq. (3.12) -in dynamic form with additional lagged values of productivity-is estimated using the two-step XTABOND2 system GMM approach (Arellano and Bond, 1991) implemented in STATA.

[60] The null hypothesis of the Hansen test is that all overidentifying restrictions are jointly valid. As the p-values of the Hansen test are greater than 0.1, we cannot reject the null and this implies that the instruments are valid.

[61] The optimal lag length of the dependent variable is selected until no serial correlation is achieved in residuals. For the disturbances to be not serially correlated, there should be evidence of significant negative first order serial correlation and no evidence of second order serial correlation in the differenced residuals. Hence, according to the

Table 3.2, digitalization has a positive and significant impact on TFP and TFP growth. When we look at the impact of the automation and ICT indices, we find that only ICT has an enhancing TFP effect. When looking at column (4), we can notice that for every standard deviation increase of the digitalization index, TFP would increase by more than 0.7%. This number is slightly lower than what we obtained for SMEs in Chapter 2. However, in contrast with the previous chapter, we also find a learning by trading effect (De Loecker, 2013) when considering the whole sample of firms.

Table 3.2: The effect of the digitalization index on TFP

Dependent variable:	TFP	TFP	TFP	TFP	TFP	TFP growth
	(1)	(2)	(3)	(4)	(5)	(6)
TFP_{t-1}	0.544***	0.443***	0.436***	0.446***	0.359***	-0.554***
	(0.187)	(0.147)	(0.127)	(0.101)	(0.095)	(0.101)
DIG_{t-1}	0.107**	0.098***		0.074**		0.074**
	(0.043)	(0.035)		(0.033)		(0.033)
$Automation_{t-1}$			0.014		0.009	
			(0.011)		(0.012)	
ICT_{t-1}			0.119***		0.100**	
			(0.043)		(0.039)	
Trade $status_{t-1}$				0.034*	0.033*	0.034*
				(0.020)	(0.020)	(0.020)
Firm controls	No	No	No	Yes	Yes	Yes
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,458	12,458	12,458	12,456	12,456	12456
Firms	1,984	1,984	1,984	1,983	1,983	1,983
No. of instruments	59	95	134	189	224	189
AR(1) test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test (p-value)	0.423	0.797	0.719	0.828	0.618	0.828
Hansen-J (p-value)	0.711	0.531	0.247	0.172	0.143	0.172

Notes: The dependent variable in columns (1) to (5) is the log of TFP, whereas in (6) it is the difference of the log of TFP from *t*-1 to *t*. All explanatory variables are included with one-period lag. All specifications include the second lag of TFP, industry dummies, and year dummies. Firm controls include employment, firm's age and foreign ownership. Estimates are obtained through the two-step system GMM estimator with robust standard errors corrected for finite sample bias (Windmeijer, 2005). AR(1) and AR(2) values report the p-values of the tests for first and second order serial correlation in the differenced residuals, respectively. In column (1) DIG is considered exogenous, while in the rest it is considered endogenous. We use levels of TFP, DIG, Automation, ICT, trade status and employment dated (*t*-3) to (*t*-5) as instruments in the difference equation, and differences dated (*t*-2) as instruments in the levels equation, as well as age, foreign ownership, industry dummies and year dummies. Year FE only enter in the equation in levels. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Arellano-Bond test for serial correlation presented in Table 3.2, all models show evidence of significant first-order serial correlation in differenced residuals, and none show evidence of second-order serial correlation in the differenced residuals, suggesting the overall consistency of our estimates.

3.4. Data and Descriptive Statistics

3.4.1. Data

The data, as in previous chapters, is drawn from the Survey on Business Strategies (ESEE, henceforth) for the years 2001-2014. This is a yearly panel database that began in 1990 and is financed by the Spanish Ministry of Industry, Tourism and Trade, and supervised by the SEPI foundation. Firms in the survey are representative by two-digit NACE-Rev.1 manufacturing industries and size categories. The ESEE provides data on firm's activity, including employment, products and manufacturing processes, customers and suppliers, costs and prices, markets, technological activities, foreign trade, and accounting data. As explained in Chapter 2, because some of the variables used to build the digitalization index first appeared in 2001, the period of analysis in chapter spans from 2001 to 2014.

Concerning the sampling of the ESEE survey, firms with less than 10 employees were initially ruled out from answering the questionnaire. Then, firms between 10 and 200 employees were randomly samples, representing around 5% of the population in 1990. Firms with more than 200 employees were surveyed on a census basis, achieving a participation rate of around 70%. Attrition has been minimized and new firms have been introduced every year in the survey with the same sampling criteria as in 1990. Thus, this dataset keeps being representative over the years.

Our initial sample consists of an unbalanced panel of 24,112 observations corresponding to 3,353 firms that have been observed in at least two consecutive periods between 2001 and 2014.

3.4.2. Descriptive Statistics

Table 3.3 shows the descriptive statistics for the dependent variable, the main variables of interest, and the remaining control variables. It is interesting to note that most workers in the sample do not have a college degree, are employed full-time, and have a permanent contract. However, it is important to highlight that the Spanish labor markets presents relatively high unemployment rates and a high proportion of temporary workers (Ortiz and Salas Fumás, 2020).

First, we plot the evolution over time of the degree of digitalization (through the composite digitalization index and its two components, namely ICT and automation) and overall employment, as well as the various categories of employment (workers' education level, contract type, etc.). At the outset, it is important to note that all-time series plotted in this section have been normalized so that the first year (2001) equals 100, since we are interested in analyzing trends.

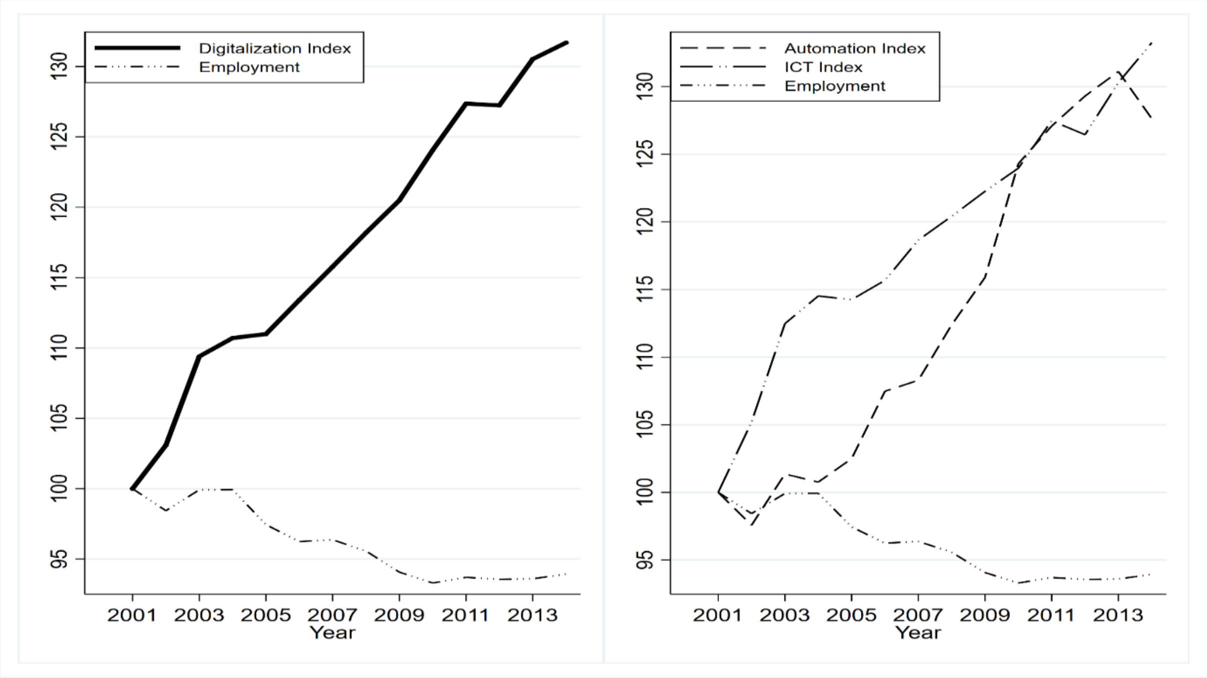
Table 3.3: Descriptive statistics

	Mean	St. Dev.	Min.	Max.	Obs.
Log Employment	4.28	1.40	0.00	9.04	16,825
Log Total Effective Hours	4.85	1.38	0.69	9.62	16,825
TFP	3.55	0.71	2.58	5.77	16,825
Markup	1.09	0.55	0.82	18.61	16,825
Log Real Average Wage	10.40	0.40	8.72	13.46	16,825
Log Total Capital	14.62	2.02	8.35	21.10	16,825
Log Skilled Employment	2.42	1.58	0.00	8.25	13,952
Export Propensity	0.70	0.46	0.00	1.00	16,825
Import Propensity	0.69	0.46	0.00	1.00	16,825
R&D Propensity	0.39	0.49	0.00	1.00	16,825
Log Price of Materials	0.00	0.00	-0.03	0.01	16,825
% of Non-Graduated	86.29	14.76	0.00	100.00	16,797
% of Graduated after a 3-Year Course	7.37	9.78	0.00	100.00	16,797
% of Engineers and Graduates	6.35	8.49	0.00	100.00	16,797
Log Part-Time Workers	1.20	1.21	0.00	6.56	5,893
Log Full-Time Workers	4.05	1.51	0.00	9.04	15,770
Log Permanent Contract Workers	4.13	1.44	0.00	9.04	15,800
Log Temporary Contract Workers	2.42	1.50	0.00	7.36	10,439
Log Employment in R&D	1.82	1.26	0.00	7.75	5,914
Log Employment in Non-Industrial Plants	2.90	1.77	0.00	8.33	3,848
DIG	0.39	0.19	0.01	1.00	16,825
ICT	0.41	0.19	0.01	1.00	16,825
Automation	0.34	0.33	0.00	1.00	16,825

Source: ESEE, 2001-2014. The sample are firms that are at least observed for two consecutive years and for which an estimate of TFP can be obtained.

In the left panel of Figure 3.1, we show how total employment in manufacturing firms and the digitalization index evolve over the 2001-2014 period, while on the right side we break down the digitalization index into the two sub-indices, the automation index and the ICT index. While the extent of digitalization has increased by more than 30% over the period, manufacturing employment has declined by around 6%. This increase in digitalization is due to both an increase in ICT and a steep automation process, particularly relevant since the second half of the 2000s. Although not shown, the behavior of total effective hours is very similar to that of employment. In the econometric specification, we will then test whether the employment decline is due to the displacement effect of digitalization.

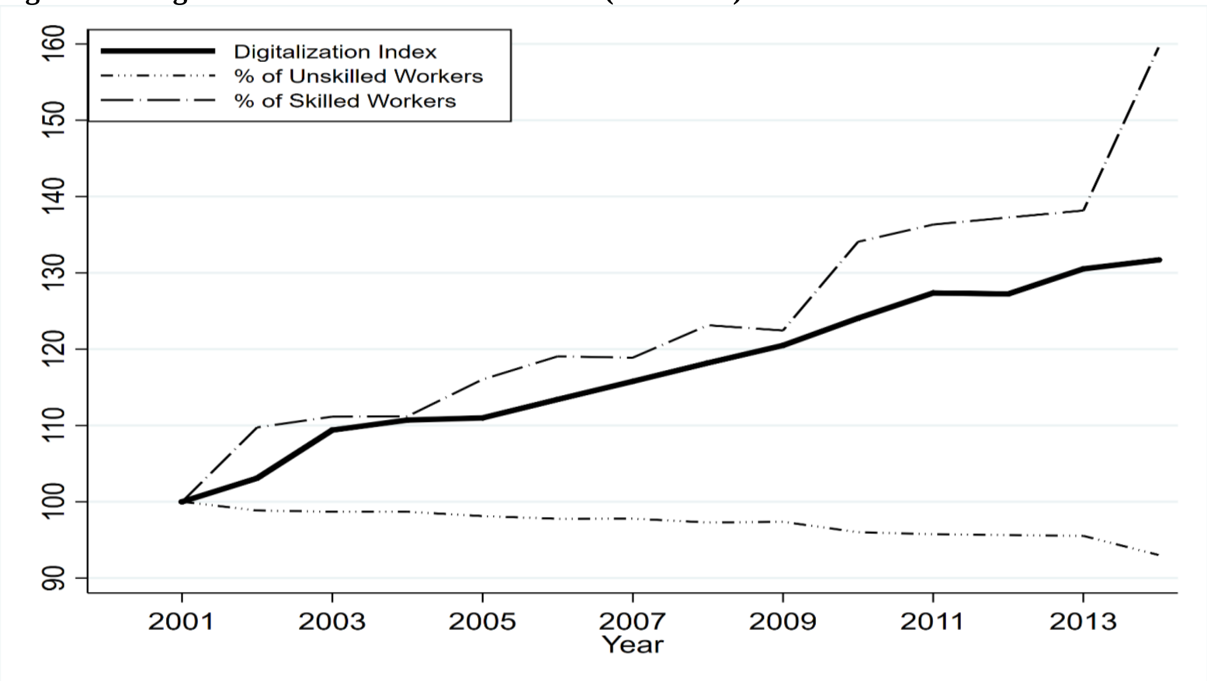
Figure 3.1: Digitalization index vs. total employment (2001=100)



Source: ESEE Dataset

Note: The automation index takes into account the use of robots, computer-aided design (CAD), local area network (LAN) and flexible systems whereas the ICT index considers ICT capital, ICT training, computer programming services, implementation of software programs, and whether the firm has its own internet domain, has its webpage in the company's servers, purchases to suppliers through internet, sells to final consumers and/or companies through internet.

Figure 3.2: Digitalization index vs. level of skills (2001=100)

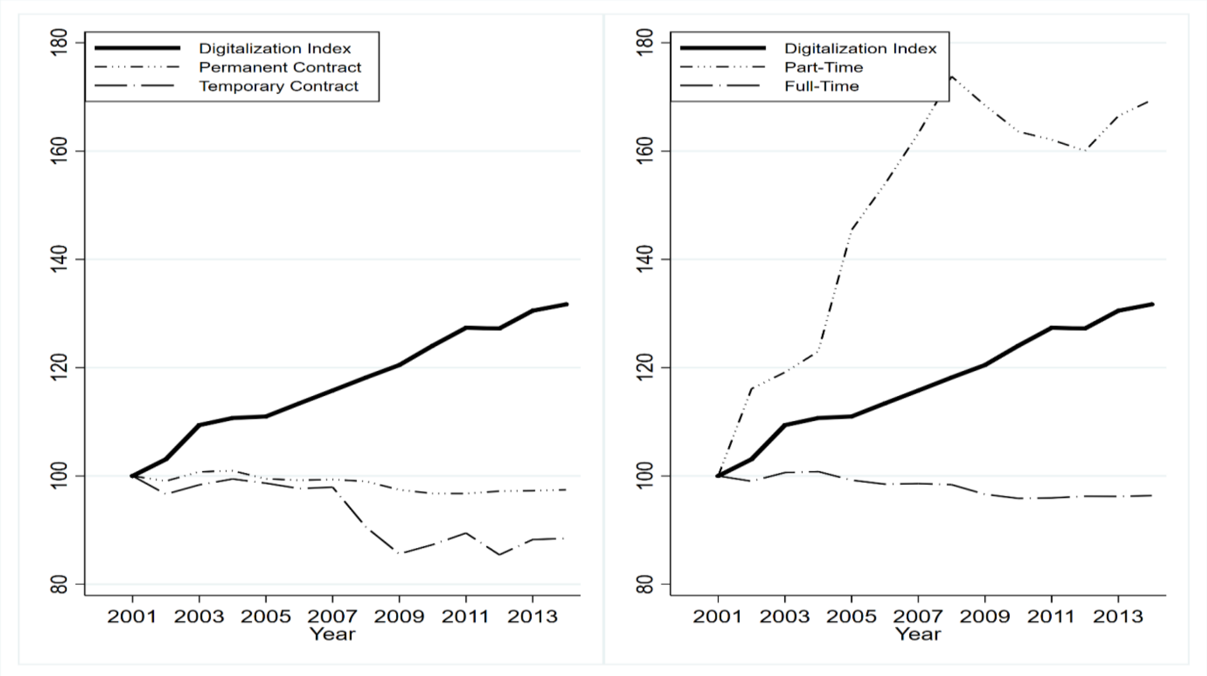


Source: ESEE Dataset

Note: Skilled workers are workers who have at least graduated from a 3-year course, a 5-year course, and engineers.

In Figure 3.2, we show how the share of workers with different skills has evolved over the years. The share of unskilled workers seems to have decreased by about 7%, while the share of skilled workers has increased by 60%. This is in line with one strand of the literature that states that workers with low skill levels suffer more from digitalization than workers with higher skill levels, as DTs would replace the former and complement the latter (Akerman *et al.*, 2015).

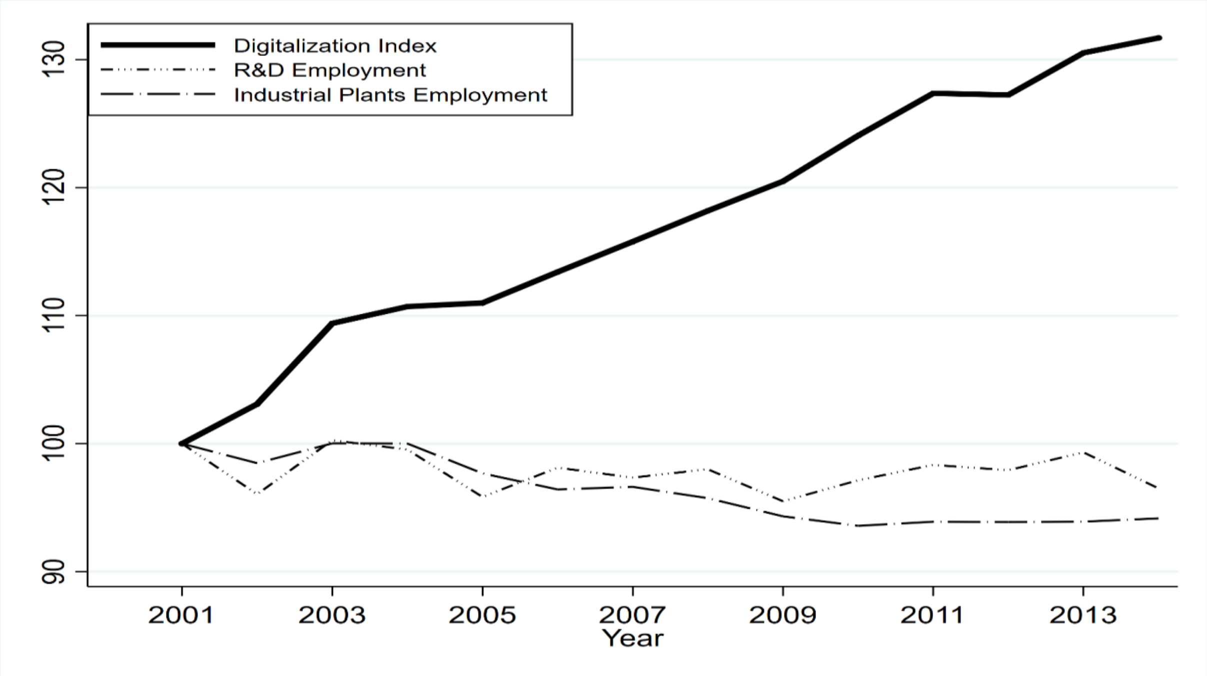
Figure 3.3: Digitalization index vs. temporary/permanent contracts, and part-time/full-time employment (2001=100)



Source: ESEE Dataset
Note: The ESEE provides information about the number of temporary contract workers, that we then subtract to total employment to obtain permanent contract workers. Part-time and full-time salaried workers are directly given in the dataset. All the variables are taken in logs and normalized.

In Figure 3.3, we divide employment into different categories: temporary and permanent contract workers on the left panel, and part-time and full-time workers on the right panel. While the employment of workers with permanent contracts remained fairly stable over the 2001-2014 period, the employment of workers with temporary contracts decreased by slightly more than 10%. Workers on fixed-term contracts suffered a sharp decline in 2008, due to the impact of the Great Recession. Turning to the right panel, although the share of workers with part-time contracts in Spain is relatively low compared to other European countries, the graph shows that their number increased by about 70% over the period analyzed, particularly before 2008. In contrast, the number of full-time employees declined slightly between 2001 and 2014, and thus appears to be negatively correlated with digitalization.

Figure 3.4: Digitalization index vs R&D and industrial plants employment (2001=100)



Source: ESEE Dataset
Note: R&D employment is measured as the number of workers in the R&D department. The number of industrial plants workers is the result of subtracting from total employment the number of non-industrial plants workers, which is provided in the dataset. All variables are taken in logs and normalized.

Finally, Figure 3.4 shows the evolution of R&D and industrial plants employment and the digitalization index over the 2001-2014 period. R&D employment decreased by about 3-4% in 2014 compared to 2001. In the case of industrial plants employment, this decline is smaller with a decrease of just over 5%. Whether this decline is the result of digitalization will be analyzed below.

It is important to remember that these graphs cannot prove any causal impact of digitalization on the employment variables. To go beyond correlations and intuitions, we need to estimate the models presented in equation (3.6) and (3.7).

3.5. Results

We now turn to assess the impact of digitalization on the labor demand of profit-maximizing firms in the Spanish manufacturing sector. To do so, we first estimate equation (3.6) using OLS fixed effects and an instrumental variable approach via 2SLS, controlling for the potential endogeneity of digitalization. We first discuss our main results before delving deeper into the effect of digitalization on the composition of employment.

3.5.1. Baseline Results

The main results are displayed in Table 3.4. In column (1), we estimate an OLS fixed effects model as a benchmark, in which we ignore the potential endogeneity of the digitalization index. In column (2), we report the same specification but using the same sample as for the IV strategy[62]. Digitalization appears to be positively and significantly related with employment regardless of the sample size. Columns (2) and (5) are the equivalents of columns (1) and (4) respectively, aside from the fact that we disentangle the digitalization index into its two sub-indices, the ICT and automation indices. The θ coefficient, which captures the combined demand-scale effect and the potential substitutability of DTs, is very similar across models in columns (1) and (2), and (4) and (5).

To account for the potential endogeneity of digitalization, we use an IV-2SLS estimation procedure. The results are presented in columns (3) and (6). In column (3), we use the digitalization index (DIG) and instrument it with its second lag, whereas the ICT and automation indices in column (6) are also instrumented with their respective second lags. We begin by discussing the first stage of the IV regression, which is reported at the bottom of the table. As shown in column (3), the instrument is positively and significantly correlated with the digitalization index in the first stage. In column (6), giving that we have two instruments for two endogenous variables, it implies that we have two first stages. Both the second lag of the ICT index and that of the automation index are positively and significantly related to the variable they instrument. Moreover, the instruments appear to be relevant as they pass both first-stage tests for weak instruments. Both the Kleibergen-Paap weak identification rk Wald F-statistic and the Cragg-Donald Wald F-statistic surpass the Stock-Yogo 10% critical values fixed at 16.38 and 7.03 for columns 3 and 6, respectively (Stock and Yogo, 2005).

[62] The IV strategy uses the second lag of the digitalization index as an instrument, therefore it has less observations.

Table 3.4: The impact of digitalization on labor demand. Baseline results

	(1) OLS-FE	(2) OLS-FE	(3) IV-2SLS	(4) OLS-FE	(5) OLS-FE	(6) IV-2SLS	
Second stage:							
Dependent variable:			*Employment (logs)*				
DIG	0.234***	0.228***	0.438***				
	(0.043)	(0.044)	(0.158)				
ICT				0.231***	0.226***	0.565***	
				(0.043)	(0.045)	(0.179)	
Automation				0.035*	0.036*	0.046	
				(0.020)	(0.019)	(0.067)	
TFP$_{t-1}$	0.377***	0.368***	0.366***	0.374***	0.365***	0.356***	
	(0.042)	(0.043)	(0.042)	(0.042)	(0.042)	(0.042)	
Markup$_{t-1}$	-0.073***	-0.066***	-0.065***	-0.072***	-0.065***	-0.062***	
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	
Real Average Wage$_{t-1}$	-0.345***	-0.341***	-0.342***	-0.345***	-0.342***	-0.345***	
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	
Capital Stock$_{t-1}$	0.194***	0.186***	0.181***	0.193***	0.186***	0.177***	
	(0.021)	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)	
R&D Propensity$_{t-1}$	0.077***	0.075***	0.073***	0.077***	0.075***	0.071***	
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	
Export Propensity$_{t-1}$	0.045***	0.043***	0.040**	0.045***	0.042***	0.037**	
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	
Price of materials$_{t-1}$	6.498**	6.679**	6.633**	6.377**	6.568**	6.266*	
	(3.126)	(3.168)	(3.161)	(3.136)	(3.179)	(3.220)	
Observations	14,540	12,964	12,964	14,540	12,964	12,964	
No. of firms	2,317	1,905	1,905	2,317	1,905	1,905	
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	
KP (F-stat.)[a]			452.731			102.343	
CD (F-stat.)[b]			905.021			244.393	
First Stage							
Dependent variable:			DIG			ICT	Automation
DIG$_{t-2}$			0.285***				
			(0.013)				
ICT$_{t-2}$						0.205***	0.049*
						(0.015)	(0.025)
Automation$_{t-2}$						0.007	0.345***
						(0.006)	(0.011)

Notes: All the specifications include year dummies. All variables, except the DIG, ICT and Automation indices, are included with one-period lag. Columns (1) and (4) consists of a fixed effects OLS model. Columns (2) and (5) also but using the sample as columns (3) and (6) where we use an instrumental variable (IV) in a 2SLS procedure. The IVs models were estimated using the Stata command ivreg2. In columns (1) and (4), robust standard errors are displayed in parenthesis. In columns (2), (3), (5) and (6), robust clustered standard errors are displayed in parenthesis. The coefficients of the instruments in the first stage can be found at the bottom of the table. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

[a] KP stands for the heteroscedasticity-robust Kleibergen-Paap Wald F test for weak instruments.

[b] CD stands for the standard non-robust Cragg-Donald Wald test for weak instruments.

While the direct effect of digitalization on employment is already sizeable in the OLS-FE models, it is nearly doubled when using a 2SLS model, reflecting the downward bias of the OLS estimates. More precisely, a one standard-deviation increase in the digitalization index corresponds to a

4.4% increase of total employment within the firm. That digitalization has a positive direct effect on firms' labor demand may be because the demand-scale effect offsets the potential displacement effect, and thus results in net job creation. It could also be because the positive demand effect is coupled with a positive supply effect arising from potential complementarities between DTs and labor.

To assess if different DTs may have a different impact on employment, we disentangle the digitalization index into the ICT and automation indices. The IV results are presented in column (6) of Table 3.4. It appears that the previous positive effect of digitalization on employment is caused by the ICT index, which has a positive and significant effect on employment, and not by the automation index, which has a positive but not significant effect. The results show that for every one standard-deviation increase of the ICT index, firms' employment is boosted by approximately 5.7%. Overall, these findings imply that automation technologies may be substitutes for employment, but their replacement effect is cancelled out by a positive demand-scale effect. On the contrary, ICT, as suggested by its positive impact on employment, has not only a positive demand-scale effect, but also may complement labor, and thus further increases employment.

The impact of digitalization on employment goes beyond the direct impact due to the combined scale and replacement effects. There is also a productivity effect of digitalization on employment captured by the coefficient of the TFP variable. The results in column (3) in Table 3.4 show that TFP has a positive and significant impact on employment, indicating that a 1% increase in TFP leads to an increase in employment by almost 0.4%. This result coupled with the fact that, as shown in Table 3.2, the digitalization index has a positive and significant effect on TFP, confirms that digitalization impacts employment in a positive way through the productivity effect. Our findings seem to contradict previous studies suggesting that digitalization has a negative effect (Mann and Püttmann, 2017; Dottori, 2021)[63] or no effect (Gaggl and Wright, 2017) on manufacturing jobs. However, it appears to go in line with studies by Stapleton and Webb (2020) and Koch *et al.* (2021), which using the ESEE dataset, show evidence of a positive effect of robotization on manufacturing employment[64].

[63] The level of analysis of Mann and Püttmann (2017) and Dottori (2021) is at the local labor markets level whereas we use firm-level data

[64] In contrast, Camiña *et al*. (2020) find a negative effect of automation technologies on manufacturing employment.

Regarding the rest of the other control variables, the markup appears to have a negative and significant effect on employment. As expected, an increase in firms' market power leads to a decline in the labor demand. Real average wages are also negatively associated with employment. According to the law of demand, the higher the price, the lower the quantity demanded (Marshall, 1920). This implies that increasing the price of the workforce, i.e., the wage, would decrease the quantity of labor demanded by employers. The coefficient of the capital stock shows positive and significant, as firms that expand their businesses tend to hire more employees[65]. Firms doing R&D are also larger. According to Bogliacino *et al.* (2011), R&D has a positive effect on employment, which is perceptible in high-tech manufacturing but absent in the more traditional manufacturing sectors. Export propensity also has a positive and significant effect on employment since an increase in export participation raises labor demand upwards (Orbeta, 2002). Producing more goods in order to export them should translate into job creation, as suggested by Tandoğan (2019) for the case of Turkey. Finally, although strikingly, the price of materials appears to be positively related to employment. The higher the price of materials, the lower their demand, which could in turn increase the labor demand in order to compensate for this lack of materials in the production process. This could be explained if the firm back-shores or integrates vertically the production process as a result of an increase in the prices of intermediates.

3.5.2. Heterogenous Employment Effects from Digitalization

To gain a better understanding of the impact of digitalization on different categories of employment, we estimate equation (3.6), but this time using other employment-related variables as dependent variable. Results are presented in Table 3.5. To estimate the model, we use a fixed effects IV-2SLS approach, in which the digitalization index is instrumented by its second lag. We formally test for the validity of the instrument. Thus, the Kleibergen-Paap Wald test and the Cragg-Donald F-statistic indicate that the instrument is not weak across all specifications.

[65] Although we do not differentiate between ICT and non-ICT capital, our results are in line with Stehrer (2022), who show that non-ICT capital has a positive impact on employment growth, while ICT capital has no effect. Giving that capital in our study considers both non-ICT and ICT, the magnitude of the overall effect on employment is coherent with the results obtained by Stehrer (2022).

In columns (1) and (2) of Table 3.5 we show that the digitalization index is positively related to both skilled and unskilled employment. A one standard-deviation increase in the extent of digitalization is associated to a 5.4% rise of skilled employment, whereas unskilled employment would increase by 4.6%. Similar to Michaels *et al.* (2014), the demand for skilled workers seems to experience a greater increase than the demand for unskilled workers in response to the digital transformation. Concerning the productivity effect of digitalization on employment, the tendency is the reversed. For a 1% increase of TFP, skilled employment raises by almost 0.2%, whereas this proportion is almost doubled for unskilled employment.

Table 3.5: Sensitivity analysis. Heterogeneous employment effects from digitalization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Second Stage: *Dependent Variable:*	Unskilled Emp.	Skilled Emp.	Manufact. Emp.	Perm. Workers	Temp. Workers	Emp. in SMEs	Emp. in Large Firms
DIG	0.464**	0.543**	0.448***	0.302*	0.549	0.570***	0.279
	(0.180)	(0.261)	(0.169)	(0.169)	(0.567)	(0.218)	(0.218)
TFP_{t-1}	0.379***	0.192***	0.372***	0.424***	0.292**	0.304***	0.604***
	(0.045)	(0.058)	(0.043)	(0.048)	(0.144)	(0.045)	(0.096)
$Markup_{t-1}$	-0.063***	-0.048**	-0.063***	-0.068***	-0.055*	-0.048**	-0.208***
	(0.021)	(0.020)	(0.021)	(0.021)	(0.032)	(0.019)	(0.067)
Real Average $Wage_{t-1}$	-0.369***	-0.116**	-0.348***	-0.265***	-0.819***	-0.318***	-0.427***
	(0.036)	(0.045)	(0.031)	(0.032)	(0.120)	(0.034)	(0.053)
Capital $Stock_{t-1}$	0.182***	0.183***	0.168***	0.185***	0.104	0.143***	0.319***
	(0.024)	(0.033)	(0.021)	(0.024)	(0.065)	(0.023)	(0.047)
R&D $Propensity_{t-1}$	0.061***	0.099***	0.066***	0.069***	0.059	0.077***	0.047**
	(0.016)	(0.028)	(0.014)	(0.015)	(0.047)	(0.016)	(0.023)
Export $Propensity_{t-1}$	0.033	0.073**	0.032*	0.038**	0.081	0.032*	0.093**
	(0.020)	(0.035)	(0.017)	(0.018)	(0.057)	(0.017)	(0.046)
Intermediate $Inputs_{t-1}$	6.859*	8.402	7.786**	4.624	15.930	4.993	12.728**
	(3.557)	(5.252)	(3.140)	(4.283)	(14.171)	(3.780)	(5.871)
Observations	12,943	12,964	12,964	12,544	7,854	9,340	3,624
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP (F-stat.)[a]	451.466	452.731	452.731	454.225	284.197	284.602	155.196
CD (F-stat.)[b]	904.246	905.021	905.021	904.104	540.179	580.837	300.878
First Stage	Digitalization index (DIG)						
DIG_{t-2}	0.285***	0.285***	0.285***	0.286***	0.285***	0.273***	0.303***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.017)	(0.016)	(0.024)

Notes: All the specifications include year dummies. All variables, except the digitalization index, are included with one-period lag. All columns include the same controls as column (3) of Table 3.4. In all columns, we use an instrumental variable (IV) in a 2SLS procedure. The first stage can be found at the bottom of the table. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

[a] KP stands for the heteroscedasticity-robust Kleibergen-Paap Wald F test for weak instruments.

[b] CD stands for the standard non-robust Cragg-Donald Wald test for weak instruments.

In column (3) of Table 3.5 we present the results for manufacturing employment. The results show that digitalization exerts both (positive) direct and productivity effects. Manufacturing employment increases by 4.5% for every one standard-deviation increase in the digitalization index, and increases by nearly 0.4% for every 1% increase in TFP. Columns (4) and (5) consider the impact of digitalization on the demand of permanent and temporary salaried workers, respectively. The results show that permanent salaried staff would increase by 3% for every standard-deviation increase of the digitalization index, whereas the effect on temporary salaried staff is not significant. However, permanent and temporary salaried staff benefit from the productivity effect of digitalization. Increasing firm's TFP by 1% leads to a rise in the number of permanent and temporary workers of around 0.4% and 0.3% increase, respectively. The effect of wages on temporary employment is the strongest when looking at all the sub-categories of employment. For every standard-deviation increase of the real average wage, temporary employment would decrease by more than 8%, whereas permanent employment would only decrease by 2.6%.

Finally, we consider the impact of digitalization on total employment in SMEs (column (6)) and large firms (column (7)). The results show that digitalization has a direct positive and significant impact on the labor demand of SMEs, whereas there is no effect on large firms' employment. For every standard-deviation increase of the digitalization index, SMEs' employment is expected to raise by 5.7%. However, the productivity effect is stronger for large firms, which translates into a 0.6% increase in labor demand for every 1% increase in TFP. For SMEs, this effect remains positive and significant, but is halved compared to their larger counterparts.

3.5.3. Impact of Digitalization on the Shares of Workers' Composition

To complement the previous analysis, we examine here the impact of digitalization on the share of employment-related variables. In doing so we estimate equation (3.7). As previously stated, we use a Generalized Linear Model (GLM) to account for the bounded nature of the dependent variable (Papke and Wooldridge, 2008), and a CF approach to account for the potential endogeneity of the digitalization index. Therefore, in a first step we regress the digitalization index on its second lag value in a FE model. We then estimate equation (3.7) using the disturbance values from the first step. The results are presented in Table 3.6 in terms of average marginal effects.

From the previous results shown in Table 3.5, digitalization had a positive and significant impact on both the demand for skilled and unskilled employment, through both the direct and productivity effect. However, this is not the case when looking at their employment shares. Indeed, in column (1) of Table 3.6, we have evidence of a negative direct impact of digitalization on the share of unskilled employment. For every one standard-deviation increase of the digitalization index, the share of unskilled employees would decrease by almost 2.5%. Column (2) shows that this negative effect is transmitted from both the ICT and automation indices. The productivity effect of digitalization also appears negative, with a 1% increase in TFP leading to a decrease in the share of unskilled employment by 0.02%. Although not reported in Table 3.6, digitalization, also through the ICT and automation indices, has a positive and significant impact on the share of skilled employment, both through the direct and productivity effects. Hence, digitalization appears to be biased towards skilled employment, which goes in line with previous studies (Akerman *et al.*, 2015; Graetz and Michaels, 2018; Humlum, 2019; Zator, 2019). Despite benefiting both skilled and unskilled workers in absolute values, the share of the latter is negatively related to digitalization, while the opposite is true for the former.

The results in columns (3) and (4) of Table 3.6 show that digitalization has no direct effect on the share of temporary workers. It seems that the negative replacement effect is offset by the positive scale effect. However, when we break down the digitalization index, we observe that ICT has a positive direct impact, whereas automation has a negative effect on the proportion of temporary workers. This may be due to the fact that ICTs may have a larger scale effect on demand than automation technologies, or the fact that automation technologies may have a larger replacement effect, or a combination of both. Nevertheless, the productivity effect on the share of temporary workers is positive. A 1% increase in TFP leads to an increase in the share of temporary workers of 0.05%.

Finally, in columns (5) and (6) of Table 3.6 we focus on the proportion of manufacturing employment[66]. First, we observe that the direct effect of digitalization is negative. The digitalization index, as well as ICT, display negative and significant coefficients. In contrast, automation has no significant impact. Results in column (5) suggest that for every one standard-deviation increase of the

[66] The share of manufacturing employment is the number of workers employed at manufacturing establishments divided by the total number of workers employed by the firm.

digitalization index, the share of manufacturing employment decreases by nearly 1.5%. There is also a negative productivity effect. A 1% increase of TFP reduces the share of manufacturing employment by 0.02%. This result is similar to that on the share of unskilled workers.

Table 3.6: The impact of digitalization on the shares of workers' composition

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Unskilled	Unskilled	Temp. Workers	Temp. Workers	Manufact. Emp.	Manufact. Emp.
DIG	-0.243***		0.005		-0.146***	
	(0.034)		(0.039)		(0.027)	
ICT		-0.194***		0.085*		-0.250***
		(0.052)		(0.051)		(0.036)
Automation		-0.058***		-0.027*		0.012
		(0.013)		(0.016)		(0.011)
TFP_{t-1}	-0.023**	-0.022**	0.054***	0.051***	-0.024***	-0.017***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.007)	(0.007)
Residual Dig.	0.192***		0.023		0.111***	
	(0.042)		(0.048)		(0.033)	
Residual ICT		0.130**		-0.073		0.207***
		(0.060)		(0.059)		(0.040)
Residual Auto.		0.059***		0.041**		-0.012
		(0.016)		(0.020		(0.014)
Observations	13,161	13,161	12,584	12,584	13,165	13,165
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak Means	Yes	Yes	Yes	Yes	Yes	Yes
CF	Yes	Yes	Yes	Yes	Yes	Yes

All the specifications include year and industry dummies. All variables, except the digitalization index, are included with one-period lag. All columns include the same controls as column (3) of Table 3.4 plus import status and the age of the firm. In all columns, we use an instrumental variable (IV) control function approach and therefore, the regressions include the residual of the first-stage estimation. Following Wooldridge (2005), within-means of the control variables are also included in the regressions (i.e., Mundlak means). CF stands for control function. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

3.5.4. Robustness Checks

In this section, we perform a series of robustness checks based on the models from columns (3) and (6) in Table 3.4 (i.e., the IV-2SLS approach).

The first robustness check, the results of which are presented in columns (1) and (2) of Table 3.7, consists of introducing more controls to check for omitted variable bias. This additional firm level controls are foreign ownership, whether the firm faces recessive and expansive markets, the number of market competitors, and the internal and external financial health[67]. The results show that the direct and

[67] Table 2A.1 in the Appendix of Chapter 2 presents a definition of these variables.

productivity effects are similar to the baseline specification. For every one standard-deviation increase of the digitalization index, total employment increases by 4.7%, compared to 4.4% in column (3) of Table 3.4. Concerning the productivity effect, employment is boosted by 0.37% for every 1% increase of TFP, compared to 0.36% previously.

Table 3.7: Robustness checks

	Additional Controls		**Alternative IV**	
	(1)	(2)	(3)	(4)
Dependent Variable:	*Employment (Logs)*			
DIG	0.472***		4.852*	
	(0.156)		(2.873)	
ICT		0.556***		3.891
		(0.181)		(2.449)
Automation		0.069		-2.146
		(0.066)		(3.785)
TFP_{t-1}	0.374***	0.364***	0.337***	0.229
	(0.047)	(0.048)	(0.074)	(0.145)
Observations	12,492	12,492	12,180	12,180
Time FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
KP (F-stat)[a]	461.803	99.529	3.447	0.292
CD (F-stat)[b]	866.894	230.240	7.797	0.755
	Bootstrapped s.e.		**Top/Bottom 1% excluded**	
	(5)	(6)	(7)	(8)
Dependent Variable:	*Employment (Logs)*			
DIG	0.465**		0.387***	
	(0.184)		(0.149)	
ICT		0.679***		0.459***
		(0.209)		(0.168)
Automation		0.004		0.054
		(0.078)		(0.064)
TFP_{t-1}	0.407***	0.390***	0.346***	0.339***
	(0.056)	(0.055)	(0.043)	(0.043)
Observations	12,988	12,988	12,699	12,699
Time FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
KP (F-stat)[a]	452.731	102.343	438.636	99.252
CD (F-stat)[b]	905.021	244.393	882.594	237.807

Notes: All the specifications include year dummies. All variables, except the DIG, ICT and automation indices, are included with one-period lag. In columns (1) and (2), some more controls have been added. Columns (3), (4), (5), (6), (7) and (8) include the same controls as column (3) of Table 3.4. In all columns, we use an instrumental variable (IV) in a 2SLS procedure. *Significant at 10%, **Significant at 5%, ***Significant at 1%.
[a] KP stands for the heteroscedasticity-robust Kleibergen-Paap Wald F test for weak instruments.
[b] CD stands for the standard non-robust Cragg-Donald Wald test for weak instruments.

In the baseline results presented in Table 3.4, the endogeneity issue was addressed using as instrument for the digitalization index its second lagged value. As a second robustness check, in columns

(3) and (4) of Table 3.7, we use as instrument the mean (excluding the value of digitalization of the focal firm) of the digitalization index by industry, region, size, year, R&D, and export status. We assume that this instrument is exogenous to the firm's labor demand. We expect a positive correlation between the average digitalization of firm's peers and the degree of firm's digitalization. We formally test for the validity of the instrument. The instrument shows significant (although at 10%) in the first stage of the 2SLS procedure and with the expected sign, as shown in Table 3A.2 in appendix 3.A. However, the results of the Kleibergen-Paap and the Cragg-Donald tests for weak instruments, shown at the bottom of Table 3.7, do not support the validity of this instrument in this case.

As a third robustness check, to control for the fact that TFP has been estimated in a first step, we perform an IV-2SLS regression but bootstrapped standard errors with 250 replications. The results are reported in columns (5) and (6) of Table 3.7 and the significancy of the digitalization index and TFP appears to persist. Indeed, the results obtained are comparable to columns (3) and (6) of Table 3.4.

Finally, to control for the bias induced by potential outliers, we trim the log of employment (i.e., the dependent variable) by removing values below the 1^{st} and above the 99^{th} percentiles. Again, the impact of digitalization and TFP is not altered by removing extreme values and the results appear to be robust.

3.6. Conclusion

A large number of studies have examined the impact of digitalization on employment with mixed results (see Table 3A.1 in the Appendix 3.A for a review of the extant literature). Indeed, DTs can act as a substitute for labor, for example, by replacing manual routine tasks with robots, resulting in a reduction in employment, a phenomenon known as the displacement effect. Alternatively, DTs can be used to complement labor, increase productivity, and result in higher value added and employment. As shown in the previous chapters, digitalization enables firms to access a broader market, increasing demand and thus employment. This is referred to as the demand-scale effect. Which effect dominates will determine the direction of the impact of digitalization on employment.

In this chapter, we examine the direct and productivity effects (via TFP) of DTs on firms' employment decisions. In doing so, we use a sample of Spanish manufacturing firms between 2001 and 2014 drawn from the ESEE dataset. To uncover the productivity effect of digitalization on employment, we assume an endogenous Markov process in which the digitalization index is allowed to influence firm's productivity. Our findings suggest that the productivity and demand scale effects outweigh the negative displacement effect. As a result, digitalization leads to net job creation in manufacturing firms both directly and through productivity.

Nonetheless, these results can vary when we consider the workforce composition. In terms of skills, we find that skilled and unskilled workers benefit directly and indirectly, via the productivity effect, from digitalization, as well as manufacturing workers and permanent contract workers. As for temporary contract workers, they only benefit from digitalization via the productivity effect. In terms of size, SME's facing an increase in their digitalization are expected to raise their employment, as they benefit from a direct and productivity effect of digitalization. In contrast, digitalization exerts only a productivity effect on the labor demand of large firms.

However, when analyzing employment shares, the above conclusions become more nuanced. For instance, if digitization were to increase, the share of unskilled workers in total employment would decrease, both due to the direct effect and productivity effect. The same can be said for the share of manufacturing workers. Both of these results are quite similar, which goes in line with the hypothesis that manufacturing workers are more likely to be unskilled. This confirms the intuition given by previous studies that digitalization is biased towards skilled employment (Akerman *et al.*, 2015; Graetz and Michaels, 2018; Humlum, 2019; Zator, 2019). This bias could increase the demand for high-skilled workers in a disproportionate way, making these workers more valuable, and therefore increase wages inequalities favoring high-skilled workers with respect to low-skilled workers. According to Juhn *et al.* (1993), an increase in the demand for skills could cause the return to skills to rise, and thus wages inequalities between low- and high-skilled workers to intensify.

From a managerial perspective, our findings offer interesting insights. First, we find no evidence of DTs hindering the employment prospects in SMEs or large firms, and this conclusion holds regardless of the skill level. The implementation of DTs may upgrade the workers' autonomy and communication with managers without raising concern about having to dismiss employees. Nevertheless, some jobs (or tasks) will most likely be replaced by machines, but only to create new jobs probably requiring the same type of skills. According to our findings, unskilled jobs will not disappear, but will grow at a slower rate than skilled jobs, which will account for a larger proportion of total jobs in manufacturing.

In addition, the results provided by this study can help policymakers to design better policies without being reluctant to promote the use of new technologies in Spanish firms with the fear that this will increase unemployment. As suggested by the findings from Chapters 1 and 2, DTs have helped Spanish firms to remain competitive in foreign markets and, as our results here show, they also lead to more employment. This points to the need to foster policies around the provision of incentives to encourage firms to adopt DTs. These incentives could take the form of subsidies or tax breaks and would help to lower unemployment as well as increase the competitiveness of Spanish firms. As we have previously explained, this is especially true for SMEs. From the side of the employees, training courses could be offered and financed by the state, in order to prepare the Spanish labor force to the potential shift towards more digital-intensive tasks. In these terms, the Next Generation EU[68] program has put in place initiatives by which the Commission funds online training courses to improve the digital skills of the European population and helps SMEs increase their online presence. More specifically, The *Digital Europe Programme* is also a new EU funding program focused on bringing digital technology to businesses, citizens, and public administrations. It aims to shape the digital transformation of Europe's society and economy, benefiting everyone, but in particular SMEs[69].

Nevertheless, our study is not without limitations. First, although the digitalization index captures many important dimensions of the digital revolution, it does not cover new uprising DTs, such as artificial intelligence, machine learning, blockchain, the Internet of Things, or 3D printing penetration. Second, an alternative instrument to the twice lagged digitalization index could render more robust results. Third, we also lack data on assets' prices, which would allow us to disentangle the direct effect of digitalization on employment into two different effects, the displacement effect and the

[68] As reflected in the Next Generation EU program, the digital transformation is one of the two large-scale challenges of our time for Europe along with the green transformation.
[69] https://digital-strategy.ec.europa.eu/en/activities/digital-programme

demand-scale effect. Currently, we are only able to identify the combination of these two effects. Furthermore, our data do not allow us to distinguish between different occupations or levels of routineness of labor tasks, which, according to previous studies (Cirillo *et al.*, 2021), is a key element that would allow us to discern which types of employment may be threatened by digitization.

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APPENDIX 3.A

Table 3A.1: Literature review

Authors	Sectors/countries	Period of analysis	Measurement of technical change	Findings (Employment)	Findings (Wages)
Local Labor Markets (LLM)					
Gregory *et al.* (2016)	238 regions in 27 EU countries	1999-2010	Routine-replacing technological change (RRTC)	- RRTC has increased labor demand by up to 11.6 million jobs - Capital replaces labor, thus RRTC has decreased labor demand by 9.6 million jobs. - It has been overcompensated by product demand and spillover effects which have together increased labor demand by 21 million jobs	
Dauth *et al.* (2017)	402 LLM in Germany	1994-2014	Robots	- No evidence that robots cause total job losses - Every robot destroys two manufacturing jobs. This loss is fully offset by additional jobs in the service sector - Negative impact on medium-skilled workers in machine-operating occupations, while high-skilled managers benefit from a positive impact	- In aggregate, robots reduce wages.
Mann and Püttmann (2017)	722 LLM in the USA	1976-2014	Automation and non-automation patents	- Automation increases jobs in service but decreases them in manufacturing	
Chiacchio *et al.* (2018)	Regional data from Finland, France,	1995-2007	Industrial robots	- Negative effect of robots on employment	- No robust and significant results on

	Germany, Italy, Spain, and Sweden			- One additional robot per 1000 workers reduces the employment rate by 0.16-0.20 percentage points - The negative effect of robots on employment is particularly prominent for workers of middle education	the impact of robots on wage growth, even within different populations and sectoral groups
Acemoglu and Restrepo (2020)	722 LLM in the USA	1990-2007	Industrial robots	- Robotization reduces employment - One additional robot per 1000 workers reduces aggregate employment to population ratio by 0.18-0.34 percentage points - Negative employment effects of robots for routine manual occupations and blue-collar occupations (low-skilled workforce) - No positive effect for high-skills workers	- Robots have a negative effect on wages - One additional robot per 1000 workers reduces aggregate wages by 0.42%
Dottori (2021)	784 LLM in Italy	1991-2016	Robots	- No negative effect of robotization on overall employment - Very weak negative effect for manufacturing industries	- Positive effect of robots on wages
Industry-Level					
Michaels *et al.* (2014)	Industry-level data from the USA, Japan, and 9 European countries	1980-2004	ICT capital divided by value added	- ICT growth is associated with a significant increase in the demand for high-skilled workers relative to medium-skilled workers - And with a significant, but smaller, increase for low-	- ICT growth is significantly associated with increases in relative wages for high-skilled workers with

				skilled workers relative to medium-skilled workers	respect to middle-skilled workers
Falk and Biagi (2017)	Industry-level data from Denmark, Finland, France, Netherlands, Norway, Sweden and the UK	2001-2010	Broadband-enabled employees, mobile internet access, enterprise resource planning (ERP) systems and electronic invoicing	- For manufacturing industries, broadband-enabled employees, mobile internet access, enterprise resource planning (ERP) systems and electronic invoicing are positively related to the share of high-skilled workers - For service industries, only the use of mobile internet is significant - Across manufacturing, the increased usage of ERP systems accounts for 30% of the increase in the share of highly skilled workers	
Graetz and Michaels (2018)	Sectoral-level data from 17 developed countries	1993-2007	Industrial robots	- Robots do not significantly reduce total employment - Robots appear to reduce the share of hours worked by low-skilled workers relative to medium-skilled and high-skilled workers	- Robot densification is associated with increases in wages
Bessen (2019)	Industry-level (textile, steel and auto) data from the USA	1810-2011	Automation	- Automation does not cause aggregate unemployment - Reallocation of employment rather than elimination	
Klenert *et al.* (2020)	Industry-level data of 28 EU countries	1995-2015	Robots	- Robot use is correlated to an increase in aggregate employment	

				- No evidence of robots reducing the share of low-skilled workers	
Dosi *et al.* (2021)	Sectoral-level data of 19 European countries	1998-2016	Disembodied and embodied technological change	- Technology positively affects employment - Demand-enhancing effects may extend to other connected markets for goods and services	
Firm-Level					
Akerman *et al.* (2015)	Firm-level data from Norway	2001-2007	Broadband internet	- Broadband adoption in firms complements skilled workers in executing non-routine abstract tasks - But it acts as a substitute for unskilled workers in performing routine tasks	- The expansion of broadband internet reinforced the wage premium to workers performing abstract tasks. - Opposite effect for jobs requiring routine tasks - A 10-percentage point increase in broadband availability raises (lowers) hourly wages of workers with abstract (routine) task intensity at the 75th percentile by 0.9 (0.2) per cent, as compared to workers at the 25th percentile of the task intensity

Gaggl and Wright (2017)	Firm-level data from the UK	2000-2004	ICT investment	- ICT raises employment in wholesale, retail and finance industries - No impact on manufacturing industries - Adoption of ICT leads to a rise in the demand for nonroutine, cognitive tasks - A modest tendency of ICT to replace routine, cognitive work while manual work seems mostly unaffected	
Dutz *et al.* (2018)	Firm-level data from Argentina, Chile, Colombia and Mexico	Argentina: 2010-2012 Chile: 2007-2013 Colombia: 2008-2014 Mexico: 2008-2013	Argentina: investment in ICT capital Chile: complex software use Colombia: high-speed internet use Mexico: internet use	- A positive effect of technologies on overall employment - Positive effects of ICT on both high- and low-skilled workers	
Dixon *et al.* (2019)	Firm-level data from Canada	2000-2015	Robots	- Investments in robots are associated with an increase in total employment within the firm - However, it can reduce middle-skilled workers employment, whereas it increases employment for low-skilled and high-skilled workers	
Humlum (2019)	Firm-level data from Denmark	1995-2015	Robots	- Robot adopters shift from low-skilled to high-skilled labor	- Robots have increased average real wages by 0.8 percent

					- Wages have decreased by 6 percent for production workers in manufacturing while tech workers have gained 2.3 percent
Zator (2019)	Firm-level data from Germany	1993-2017	Digitalization and automation	- New technologies reduce employment - Negative effects in industries such as manufacturing, retail and hospitality, but in industries such as finance and education and health, technology seem to complement workers and lead to increased employment - Both digitalization and automation increase the share of high-skill workers while the substitution effect of new technologies affects mostly unskilled workers	
Aghion *et al.* (2020)	Firm-level data from France	1994-2015	Automation	- Positive effect of automation on employment - No significant effect of automation on employment when considering firms with low exposure to international competition	
Babina *et al.* (2020)	Firm-level data from the USA	1999-2007	Investment in AI technologies	- Firms investing more in AI experience faster growth in employment	

Cusolito *et al.* (2020)	Firm-level data from 82 developing countries	2002-2019	Email and website adoption	- DTs adoption increases firms' demand for labor	
Cirillo *et al.* (2021)	Occupation-level data from Italy	2011-2016	Digital use index: use of computers and emails Digital tasks index: software programming or database administration for instance	- Employment tends to increase in highly-digitalized jobs - Negative effect for jobs that are both highly digitalized and routinized	
Evidence for Spain					
Camiña *et al.* (2020)	Manufacturing firm-level data from Spain	1991-2016	Robots, flexible production systems, data-driven control	- Negative effect of automation on employment - Since the 2000s, still a negative effect but slightly attenuated - Automation technologies, when paired with human capital, increase employment in the long-term	
Stapleton and Webb (2020)	Manufacturing firm-level data from Spain	1990-2016	Robot adoption	- Weak positive impact on total employment - Adoption doubles the number of engineers and graduates and increases production employment by 80% - No effect on the number of non-graduates or administrative workers	
Koch *et al.* (2021)	Firm-level data from Spain	1990-2016	Robot adoption	- Adoption leads to net job creation - Adopting firms increase employment compared to	- The average wage in firms adopting robots increases if the firm changes the

	non-adopters in the same industry - Positive effects on employment for high-skilled workers, but also low-skilled workers and those employed in the firm’s manufacturing establishments	composition of its workforce by hiring relatively more high-skilled workers

Table 3A.2: Robustness (first stage)

Additional Controls (1)			
First Stage	DIG	ICT Index	Automation Index
DIG_{t-2}	0.285***		
	(0.013)		
ICT $Index_{t-2}$		0.204***	0.053**
		(0.015)	(0.025)
Automation $Index_{t-2}$		0.006	0.347***
		(0.006)	(0.011)
Alternative IV (2)			
First Stage	DIG	ICT Index	Automation Index
Average DIG	0.029*		
	(0.016)		
Average ICT		0.021	0.024
		(0.016)	(0.033)
Average Auto.		0.017*	-0.011
		(0.009)	(0.023)
Bootstrapped s.e. (3)			
First Stage	DIG	ICT Index	Automation Index
DIG_{t-2}	0.306***		
	(0.020)		
ICT $Index_{t-2}$		0.235***	0.059*
		(0.021)	(0.035)
Automation $Index_{t-2}$		0.012	0.336***
		(0.008)	(0.020)
Top/Bottom 1% excluded (4)			
First Stage	DIG	ICT Index	Automation Index
DIG_{t-2}	0.284***		
	(0.014)		
ICT $Index_{t-2}$		0.205***	0.052**
		(0.015)	(0.026)
Automation $Index_{t-2}$		0.007	0.343***
		(0.006)	(0.011)

Notes: This table consists of the first stages of the 2SLS regressions performed in Table 3.7. In the first specification some more controls have been added. The other specifications include the same controls as column (3) of Table 3.4. In the second specification, we use the average (excluding the firm) of the digitalization index by year, industry, region and R&D status are used as instrument for DIG in *t*. In the third specification, we report block bootstrapped standard errors (s.e.) at firm level in parentheses (250 replications). In the last specification, the dependent variable is trimmed at the 1st and 99th percentiles. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

APPENDIX 3.B

The Labor Demand Function

The labor demand presented in equation (3.5) comes from a profit maximization problem which is formulated as follows (subscripts for firms *i* and for time *t* are suppressed for clarity reasons):

$$Max_{K,L,M}\ \pi = BQ^{\mu} - rK - wL - cM \tag{3B.1}$$

$$Subject\ to\ Q = AK^{\alpha}L^{\beta}M^{\gamma}$$

where *K* is capital, *L* is labor, and *M* is intermediate inputs. α, β, and γ are output elasticities parameters with respect to each input and c, w, and *i* are the costs of each input, respectively. Moreover, ε is the (assumed) constant price elasticity of demand. The inverse demand function is $p = D^{1/\varepsilon}Q^{-1/\varepsilon}$. Thus, total revenue is given as $R = pQ = BQ^{\mu}$, where $B = D^{1/\varepsilon}$ and $\mu = \frac{\varepsilon-1}{\varepsilon}$. The optimal solutions of (3B.1) are:

$$L = B^{\frac{1}{1-\beta\mu}}\,\mu^{\frac{1}{1-\beta\mu}}\,\beta^{\frac{1}{1-\beta\mu}}\,A^{\frac{\mu}{1-\beta\mu}}\,K^{\frac{\alpha\mu}{1-\beta\mu}}\,M^{\frac{\gamma\mu}{1-\beta\mu}}\,w^{\frac{-1}{1-\beta\mu}} \tag{3B.2}$$

$$K = B^{\frac{1}{1-\alpha\mu}}\,\mu^{\frac{1}{1-\alpha\mu}}\,\alpha^{\frac{1}{1-\alpha\mu}}\,A^{\frac{\mu}{1-\alpha\mu}}\,L^{\frac{\beta\mu}{1-\alpha\mu}}\,M^{\frac{\gamma\mu}{1-\alpha\mu}}\,r^{\frac{-1}{1-\alpha\mu}} \tag{3B.3}$$

$$M = B^{\frac{1}{1-\gamma\mu}}\,\mu^{\frac{1}{1-\gamma\mu}}\,\gamma^{\frac{1}{1-\gamma\mu}}\,A^{\frac{\mu}{1-\gamma\mu}}\,K^{\frac{\alpha\mu}{1-\gamma\mu}}\,L^{\frac{\beta\mu}{1-\gamma\mu}}\,c^{\frac{-1}{1-\gamma\mu}} \tag{3B.4}$$

Equations (3B.2), (3B.3) and (3B.4) give the profit-maximizing demand for labor, capital inputs and intermediate inputs respectively. Then substituting (A3) into (A1) and (A2), we obtain:

$$L = B^{\frac{1}{1-\mu(\beta+\gamma)}}\,\mu^{\frac{1}{1-\mu(\beta+\gamma)}}\,\beta^{\frac{\mu\gamma-1}{\mu(\beta+\gamma)-1}}\,A^{\frac{-\mu}{\mu(\beta+\gamma)-1}}\,K^{\frac{-\alpha\mu}{\mu(\beta+\gamma)-1}}\,w^{\frac{1-\mu\gamma}{\mu(\beta+\gamma)-1}}\,c^{\frac{\mu\gamma}{\mu(\beta+\gamma)-1}}\,\gamma^{\frac{-\mu\gamma}{\mu(\beta+\gamma)-1}} \tag{3B.5}$$

$$K = B^{\frac{1}{1-\mu(\alpha+\gamma)}}\,\mu^{\frac{1}{1-\mu(\alpha+\gamma)}}\,\alpha^{\frac{\mu\gamma-1}{\mu(\alpha+\gamma)-1}}\,A^{\frac{-\mu}{\mu(\alpha+\gamma)-1}}\,L^{\frac{-\beta\mu}{\mu(\alpha+\gamma)-1}}\,r^{\frac{1-\mu\gamma}{\mu(\alpha+\gamma)-1}}\,c^{\frac{\mu\gamma}{\mu(\alpha+\gamma)-1}}\,\gamma^{\frac{-\mu\gamma}{\mu(\alpha+\gamma)-1}} \tag{3B.6}$$

Finally, substituting (3B.6) into (3B.5), knowing that $B = D^{1/\varepsilon}$ and $\alpha + \beta + \gamma = \delta$, and taking logs, we obtain equation (3.5), which is the labor demand.

Conclusion

Digital technologies (DTs) have spread rapidly over the last decades and have had a profound impact on the way business operate and make decision. One key aspect of this impact is the ability of DTs to automate certain tasks, which can accelerate the production process and reduce costs. This has made it possible for firms to become more competitive and expand into new markets. In addition, DTs have facilitated communication within companies and increased the autonomy of workers. The expansion of DTs has allowed to reduce the cost of searching, matching and communicating, the costs of moving merchandises, and the costs of management and monitoring (Venables, 2001). These costs reductions allowed by digitalization have been one of the triggers for globalization, allowing businesses to quickly and easily access new markets and expand their customer and supplier base beyond local markets. The overall effect of this digitalization process has been to increase global trade. Our results presented in Chapters 1 and 2 are proof that digitalization has a positive effect on both exports and imports. As DTs continue to evolve and become more advanced, it is likely that they will continue to play a key role in shaping the global economy.

First, in Chapter 1, we have focused on the effect of information and communication technologies (ICTs) use on exports participation and export intensity. More specifically, a firm is considered an ICT user if it uses a website or engages in online transactions by selling to other firms or final consumers online, or by purchasing goods or services online. In this first chapter we focus specifically on the importance of basic ICTs and applications, as without them, the next levels of advanced DTs are impossible. The data used comes from the ESEE database of Spanish manufacturing firms for the 2000-2014 period. As a contribution to the literature, we unravel not only the direct effect of ICT use on export activities, but also the indirect effect, via productivity. In this perspective, and through the thesis, we work with an endogenous Markov process that allows digitalization to impact future productivity. Our findings suggest that ICT users are more likely to engage in exports activities, whereas using ICT has no effect on the intensity of these activities. Digitalization also has an indirect effect, via TFP, on both export participation and intensity. An interesting finding of this chapter and a motivation for the next one is that SMEs appear to benefit from digitalization in a greater way than their larger counterparts in terms of export participation. Therefore, in Chapter 2, we decide to focus only on SMEs and build an index capturing the digital transformation in a more exhaustive way. Moreover, instead of focusing only on exports, we also include imports in our analysis and assume that these two decisions are interdependent. The results here suggest that digitalization influences the decision to trade in a positive way both directly and indirectly, via productivity. Nevertheless, the direct effect of digitalization is larger for exports than imports, while the opposite is found for the indirect effect. The results in Chapters 1 and 2 are in line with existing literature, which using different methods and data find a positive impact of digitalization on exports (Kneller and Timmis, 2016; Fernandes *et al.*, 2019). Not only large firms benefit from digitalization but also SMEs (see, for instance, Hamill and Gregory, 1997; Loane, 2005; Mostafa *et al*., 2005; Hagsten and Kotnik, 2017; Añón Higón and Driffield, 2011). Literature on the effects of digitalization on imports is much scarcer but still evidences a positive impact of digitalization on imports participation (Nath and Liu, 2017; Ozcan, 2018; Stapleton and Webb, 2020; Alguacil-Marí *et al.*, 2022).

Nonetheless, despite the positive impact of digitalization on trade and hence, their positive demand enhancing effect, DTs can act as a substitute for labor, as they are able to replace humans in some tasks, as, for instance, routine tasks, which can be more easily automated. The effect of DTs on employment is thus uncertain and the last chapter of this thesis has focused on this issue. Results show that digitalization leads to net job creation as the demand-scale effect outweighs the potential replacement effect. In addition, digitalization also has a positive effect on employment through the productivity effect. The overall effect of digitalization remains positive regardless of skills and whether it is manufacturing employment or not. Unlike the overall consensus in the literature on the role of digitalization as trade facilitator, there is more controversy in terms of the direction of the effect of digitalization on employment. While some argue that digitalization will increase labor demand (see, for instance, Gregory *et al.*, 2016; Aghion *et al.*, 2020), others argue that it will have a negative impact on employment (see, for instance, Chiacchio *et al.*, 2018; Acemoglu and Restrepo, 2020). Still others claim that the impact of DTs on employment depends on a variety of factors, such as the level of skill required for a particular job, the industry in which the job is located, and the level of routineness involved in the job tasks (see, e.g., Gaggl and Wright, 2017; Akerman *et al.*, 2015; Cirillo *et al.*, 2021). Our results tend to go in line with those studies that evidence a positive effect of digitalization on total employment. However, our results support also the argument that digitalization is biased toward high-skilled employment, as it tends to increase the proportion of high-skilled employees in total employment, hence decreasing the share of low-skilled employment. Hence, DTs help to create new tasks for all skills levels, although a higher proportion of these new tasks would require high skills.

The results obtained throughout this thesis may have significant managerial implications. Firms, particularly SMEs, can increase their probability to export and import by adopting DTs, particularly basic ICT applications such as a website, as shown in Chapter 1. Digitalization helps SMEs to overcome the resource disadvantage they have in comparison to their larger counterparts. Indeed, DTs enable firms to reduce costs and advertise their products worldwide in order to reach further customers. Moreover, as seen in Chapter 3, the process of digitalization can be realized without the concern of having to reduce total employment because of some tasks being automated by new technologies. The destructions of tasks replaced by machines is more than offset by the creation of new tasks requiring the same type of skills. However, it is important to specify that, according to our results, skilled jobs will be led to represent a higher proportion of total jobs at the expense of unskilled jobs.

As for the policy recommendations, the results presented here clearly show that digitalization improves Spanish competitiveness in the foreign markets without hindering local employment. For these reasons, firms should be incentivized to move towards a higher level of digitalization. Subsidies or tax breaks would encourage firms to adopt DTs and promote the digital transformation of the economy. This government support may be particularly important for SMEs, which are under greater financial pressure than larger firms and are lagging behind in terms of the integration of new technologies[70]. Towards these ends, the SME digitalization plan 2021-2025[71] has been developed in order to boost the basic and more innovative digitalization of SMEs. These incentives could help SMEs to enter foreign markets and gain competitiveness. Moreover, digitalization has an overall positive effect on firms' employment. However, as reported in the last chapter, DTs are biased towards high-skilled labor, which

[70] https://digital-strategy.ec.europa.eu/en/policies/desi-spain
[71] https://portal.mineco.gob.es/RecursosArticulo/mineco/ministerio/ficheros/210902-digitalisation-smes-plan.pdf

could increase disproportionally their demand, making them more valuable, and thus deepen wages inequalities favoring high-skilled workers with respect to low-skilled workers. In this sense, according to Juhn *et al.* (1993), when the demand for skills increases, the return to skills increases as well, and wages inequalities between low- and high-skilled workers deepen. Therefore, training courses should be offered in order to prepare the transition towards these new tasks. In this line, the Next Generation EU program has put in place initiatives to fund online training course to improve digital skills in order to help SMEs increase their online presence and make online education more accessible. At national level, the Digital Spain 2026[72] strategy aims to invest in infrastructures, such as broadband connectivity, AI, or 5G, promote the digitalization of the economy, with a special focus on SMEs, and improve the digital skills of the Spanish population.

Overall, the key to supporting the digital transformation of the economy is to adopt a holistic approach that takes into account the needs of both firms and workers. By providing support for firms to adopt digital technologies and for workers to acquire the skills they need to succeed in the digital economy, policy makers can help ensure that the benefits of digitalization are widely shared and that the economy can continue to thrive in the digital age.

Nevertheless, this thesis is not without limitations that could provide interesting suggestions for future research. For instance, data on exports destination and imports provenance would allow us to verify the hypothesis of the *death of distance* where the digital transformation helps to remove traditional geographical barriers and makes it more accessible to export to and import from more distant countries. The digitalization index built in Chapter 2 captures several dimensions of the digital transformation, as well as numerous DTs, and is representative of the technological progress over the period of analysis (2000-2014). However, information on Industry 4.0 technologies, such as AI, machine learning, 3D printing, etc. would allow us to capture the digital transformation in a more exhaustive way and see whether their adoption has allowed to accelerate or slowdown the globalization process. Specifically in Chapter 3, we lack data on assets' prices which would allow us to disentangle the demand-scale effect

[72] The Digital Spain 2026 strategy is aligned with the EU Digital Compass, the reference framework that should guide the EU's digital transformation until 2030. https://espanadigital.gob.es/sites/espanadigital/files/2022-08/Digital%20Spain%202026-Executive%20Summary.pdf.

from the potential replacement effect of DTs on employment. Additionally, the data do not provide information on different occupations or levels of routineness of labor tasks, which is an important element determining which groups of workers are more threatened by digitalization. This data could be used to see whether routine jobs are more at risk of automation than non-routine jobs. Moreover, data on the level of routineness of tasks could be paired with data on skills levels in order to detect if routine jobs are more likely to be automated even if they require high skills.

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