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# Internationalisation, Global Value Chains and Firm Performance

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*A mi familia*

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# Resumen

Esta tesis doctoral presenta un análisis en profundidad de las estrategias de internacionalización de las empresas con especial énfasis en la participación en las Cadenas Globales de Valor (CGV). De este modo, el objetivo principal de la tesis es presentar un estudio exhaustivo de la internacionalización y las CGV desde una perspectiva a nivel de empresa. Para ello, examinamos en primer lugar cómo las estrategias de internacionalización pueden afectar en ciertas dimensiones a las empresas. Y posteriormente, nos adentramos en el debate sobre las tendencias recientes de la globalización, analizando la conexión entre la expansión de las nuevas tecnologías y las estrategias de relocalización ("*reshoring")*.

En particular, en los tres primeros capítulos exploramos cómo la internacionalización, especialmente en el contexto de las CGV, puede contribuir a un mejor funcionamiento de las empresas. En primer lugar, comenzamos abordando uno de los principales retos para las economías, el desempleo, un problema que se acentúa en tiempos de crisis. Así, en el Capítulo 1 se investiga el papel moderador de las exportaciones en la destrucción de empleo asociada a contextos recesivos de la demanda interna, usando España como caso de estudio. En segundo lugar, en el Capítulo 2, se aborda otra cuestión de especial interés. En este caso, se trata de algo que impide el crecimiento de la Productividad Total de los Factores (PTF) y el crecimiento de la producción agregada: la asignación ineficiente de los recursos ("*misallocation"*). Por lo tanto, en este capítulo se examina si la participación en las CGV puede contribuir a aliviar la *misallocation* de insumos intermedios. Además, probamos esta hipótesis específicamente para empresas españolas.

En tercer lugar, el Capítulo 3 considera que las CGV representan una oportunidad para que los países en desarrollo se incorporen a los mercados globales (Kowalski et al., 2015; Stamm, 2004). Pueden unirse a ellas y ahorrarse décadas de inversión en la formación de sus propias cadenas de suministro (Baldwin, 2013). En especial, los países africanos han sido especialmente dinámicos en los últimos años, con un crecimiento del comercio superior al de la mayoría de las economías. Por lo tanto, este capítulo identifica los factores determinantes y los efectos de la participación en las CGV por parte de las empresas manufactureras de la región.

Finalmente, para el último capítulo, reconocemos las tendencias recientes de la globalización y el debate actual sobre la ralentización ("*slowbalisation*") del comercio y las cadenas de valor. Por tanto, dado que las nuevas tecnologías pueden facilitar el *reshoring* (Rodrik, 2018), examinamos cómo la creciente utilización de robots (la principal tecnología de automatización en la industria manufacturera) ha contribuido a la tendencia actual de las CGV en España.

A lo largo de toda la tesis, utilizaremos datos a nivel de empresa. La internacionalización es, en última instancia, una estrategia de las empresas y, especialmente en el caso de la participación en las CGV, existe un interés creciente por los estudios que la captan a este nivel de decisión. Además, el uso de este tipo de datos ayuda a superar problemas derivados del uso de datos más agregados, como la insuficiente variabilidad en el análisis de regresión, la presencia de sesgos de agregación o la imputación de algunos datos en las tablas input-output de algunos países.

En los Capítulos 1, 2 y 4, que se centran específicamente en España, utilizamos un conjunto de datos de panel a nivel de empresa obtenidos de la Encuesta Sobre Estrategias Empresariales (ESEE). La ESEE es una encuesta anual, patrocinada por el Ministerio de Industria español y realizada por la Fundación SEPI, que es representativa (por industria

y tamaño) del sector manufacturero en España. Para el Capítulo 3 utilizamos datos a nivel de empresa procedentes de la Encuesta de Empresas del Banco Mundial para los sectores manufactureros de 18 países del África Subsahariana.

El estudio de las estrategias de internacionalización de España resulta especialmente atractivo. En primer lugar, a partir de la crisis de 2008 se produjo un crecimiento espectacular de las exportaciones que se ha acuñado como el "milagro español" (Eppinger et al., 2017). Además, en lo que respecta al comercio de productos intermedios, que está directamente relacionado con las CGV (Antràs, 2020), España se sitúa entre los 10 primeros países de la UE en términos de importaciones de productos intermedios. De hecho, estas importaciones de productos intermedios casi se han duplicado desde el año 2000 (European Commission, 2022). De ahí el interés de estudiar cómo estas actividades comerciales benefician y repercuten sobre las empresas.

El Capítulo 1 se centra en el significativo aumento de las exportaciones experimentado en España desde 2008, especialmente en el caso de las PYMEs. Esto es digno de mención porque, durante el mismo periodo, la economía española se vio gravemente afectada por la Gran Recesión, lo que provocó un pronunciado descenso del Producto Interior Bruto (PIB) y un impacto significativo en la demanda interna. Además, esta recesión económica provocó un aumento sustancial del desempleo. Por lo tanto, con este escenario, nuestro principal objetivo es investigar el papel moderador de las exportaciones en la destrucción de empleo asociada a contextos recesivos de la demanda interna utilizando las PYMEs manufactureras españolas como caso de estudio.

Para abordar esta cuestión, estimamos en primer lugar una ecuación de exportación, en la que analizamos si se cumple la hipótesis del "*venting out*"[1] y, por tanto, nos ayuda a

[1] La hipótesis de "venting out" es la sustituibilidad de la demanda interna por las exportaciones.

explicar el efecto moderador antes mencionado. Además, comprobamos si se cumple la predicción de Almunia et al. (2021), según la cual las empresas con mayor capacidad de producción utilizada son las que más reaccionan ante una caída de la demanda interna, convirtiéndose en exportadoras. Para ello, incluimos medias pre-muestra de la variable dependiente en la ecuación de estimación para hacer frente a la heterogeneidad individual no observada correlacionada e implementamos una corrección de selección en dos etapas de Heckman (1979) para corregir por el desgaste no aleatorio de la muestra debido a la observabilidad de las decisiones de exportación de las PYMEs solo para las empresas que continúan operando. En segundo lugar, para responder a la pregunta principal del capítulo, estimamos una ecuación dinámica de empleo.

Obtenemos que las PYMEs exportadoras muestran una mayor resiliencia en términos de empleo en un periodo de recesión que las PYMEs no exportadoras. Además, este efecto compensatorio de las exportaciones sobre el empleo favorece a los trabajadores indefinidos, siendo estadísticamente no significativo para los trabajadores temporales. Esto implica que la proporción de trabajadores fijos frente a temporales aumenta para las PYMEs durante los periodos recesivos. Además, la exportación aumenta las posibilidades de supervivencia de las PYMEs. Por último, proporcionamos más pruebas que apoyan que la participación de las PYMEs en las exportaciones también obedece a una reacción a la caída de la demanda interna (la llamada hipótesis del "venting out"). Asimismo, confirmamos la predicción teórica de Almunia et al. (2021), según la cual las empresas con una mayor capacidad de producción utilizada son las que más pueden beneficiarse adaptándose a corto plazo a la caída de la demanda interna.

Consideramos que las principales contribuciones de este capítulo son las siguientes. En primer lugar, aporta nuevas pruebas a la literatura que explora a nivel de empresa los efectos de las exportaciones sobre el empleo. En segundo lugar, ayuda a comprender el

papel de las decisiones de exportación de las empresas a la hora de mitigar el desempleo cuando una recesión doméstica afecta a la economía. En tercer lugar, se centra especialmente en las PYMEs, el grupo de empresas más vulnerable en una crisis. En cuarto lugar, profundiza en los efectos composicionales sobre el empleo en relación con los distintos tipos de contratos (indefinidos y temporales), para eventualmente ofrecer recomendaciones políticas no solo sobre cómo mitigar la caída del empleo tras un shock, sino también sobre cómo mejorar su calidad en términos de duración de los contratos. Por último, y en relación con la hipótesis de "*venting out*" ya contrastada en algunos trabajos anteriores, se ha ido un paso más allá y se ha contrastado directamente la predicción relacionada con la utilización de la capacidad de las empresas en el modelo teórico de Almunia et al. (2021).

Podemos extraer de este Capítulo varias recomendaciones políticas para las PYMEs. Dado que, por un lado, la exportación en periodos recesivos ha ayudado a las PYMEs a compensar el efecto negativo de la recesión *per se* en sus niveles de empleo y, por otro, también ha sido una buena estrategia para la supervivencia de las PYMEs, las políticas públicas deberían facilitar esta actividad entre las PYMEs. Por ejemplo, según nuestros resultados para la ecuación de exportación, esto puede hacerse promoviendo actividades de innovación entre las PYMEs, aliviando sus restricciones financieras, facilitando su acceso a los mercados exteriores o aumentando su competitividad mediante la promoción de políticas de mejora de la productividad. Estas políticas no solo ayudarían a compensar las pérdidas de empleo sufridas por las PYMEs en periodos recesivos, sino que, además, según nuestros resultados, favorecerían el empleo indefinido frente al temporal, lo que puede ayudar a paliar la inestabilidad y precariedad del mercado laboral español.

A continuación, el Capítulo 2 profundiza en las CGV en España y explora el papel que pueden desempeñar en la mitigación de la *misallocation*. En primer lugar, la *misallocation* de los factores de producción se produce cuando los recursos disponibles se distribuyen de forma ineficiente entre las empresas. Esta ineficiencia obstaculiza el crecimiento de la producción agregada. Dado que resulta de la reasignación de los factores de producción sin variar la cantidad de insumos, tiene implicaciones directas para el crecimiento de la Productividad Total de los Factores (PTF). Por lo tanto, el estudio de la *misallocation* de factores es relevante no solo por sus implicaciones para la producción agregada, sino también para el crecimiento de la PTF.

En particular, nuestra hipótesis de trabajo postula que una mayor participación en las CGV podría ser un factor clave que contribuya a una asignación más eficiente de los insumos intermedios. Hasta donde sabemos, este aspecto concreto sigue sin explorarse en la literatura existente. Las CGV están estrechamente relacionadas con el comercio de bienes intermedios (Antràs, 2020). En consecuencia, las empresas que participan en las CGV disfrutan de ventajas claras a la hora de acceder a insumos intermedios (Halpern et al., 2015; Máñez et al., 2020; Máñez Castillejo et al., 2020). A diferencia de las que dependen únicamente del abastecimiento nacional, estas empresas están menos limitadas geográficamente, lo que les permite una mayor flexibilidad para adaptarse a las fricciones del mercado que puedan surgir en mercados específicos.

Realizamos este análisis para España, ya que su economía fue testigo de una mejora en la evolución de los niveles de productividad agregada desde 2009, acompañada de una mayor participación en las CGV y una reducción de la mala asignación de los insumos intermedios.

Para estudiar el vínculo entre las CGV y la *misallocation* de insumos intermedios, aplicamos la metodología de Petrin y Sivadasan (2013) para estudiar la *misallocation*

desde el punto de vista de las empresas. Proponen calcular una brecha ("*gap*"), en la que utilizan datos de producción para estimar las diferencias entre el valor del producto marginal de un insumo y su coste marginal. Además, construimos dos indicadores principales de las CGV que identifican el margen extensivo e intensivo de participación en las CGV. Se trata del Valor Añadido Exterior (*Foreign Value Added* - FVA), que identifica el contenido de las importaciones intermedias incorporado en las exportaciones, y el Valor Añadido Indirecto (*Indirect Value Added* - IVA), que representa el valor añadido nacional en los insumos enviados a terceras economías para su posterior transformación y exportación a través de cadenas de valor.

A continuación, comenzamos aplicando Mínimos Cuadrados Ordinarios (MCO) y efectos fijos bidireccionales (*two-way fixed effects – TWFE*) para ver la relación entre la participación en las CGV y la *misallocation* de insumos intermedios. Sin embargo, reconocemos las limitaciones de estos métodos de estimación, por lo que explotamos la variación en los tiempos de tratamiento, ya que las empresas pueden ser tratadas en diferentes momentos. Es decir, las empresas empiezan a participar en las CGV en distintos momentos. Para ello, nos basamos en la configuración de Callaway y Sant'Anna (2021) y aplicamos un estimador de diferencias en diferencias (DiD) con adopción escalonada. Además, aplicamos un enfoque DiD con intensidad de tratamiento continua, explotando la aparición y expansión de la tecnología TIC basada en fibra óptica que facilita las operaciones de las CGV. Con todos estos métodos, corroboramos nuestra hipótesis. Es decir, constatamos que la participación en las CGV contribuye a aliviar la *misallocation* de insumos intermedios.

Contribuimos a la literatura sobre el estudio de la *misallocation* añadiendo varias novedades. En primer lugar, en este trabajo nos centramos en el estudio de la *misallocation* de los insumos intermedios, mientras que los trabajos anteriores se

centraban en el capital o el trabajo. De esta forma, somos capaces de desentrañar un factor que ayuda a reducir la *misallocation* de los intermedios: la participación en las CGV. En segundo lugar, con respecto a estudios anteriores sobre este tema para la economía española, ampliamos el ámbito temporal del análisis, ya que otros trabajos se centraban principalmente en la *misallocation* en el período anterior a la Gran Recesión. En tercer lugar, y en contraste con los trabajos para España y la mayoría de los trabajos para otros países, realizamos el análisis desde una perspectiva a nivel de empresa, mientras que otros trabajos tenían un punto de vista más agregado. Por último, nuestra base de datos nos permite utilizar deflactores de producción e insumos a nivel de empresa, mientras que otros trabajos utilizan deflactores industriales, lo que puede introducir un sesgo en las estimaciones de las elasticidades de los factores de producción en la función de producción.

Dado que la *misallocation* de los factores de producción afecta no solo a la producción agregada de la economía, sino también al crecimiento de la PTF, este Capítulo puede ayudar a los responsables políticos a descubrir las razones que la explican. En particular, las políticas comerciales deberían tener en cuenta que la participación en las CGV contribuye a reducir la *misallocation*. Por lo tanto, una restricción al funcionamiento de las CGV debe tomarse con cautela, ya que puede tener un efecto disuasorio sobre la asignación eficiente de los recursos y, por lo tanto, sobre el crecimiento de la PTF y la producción. En otras palabras, las implicaciones de la participación en las CGV sobre la *misallocation* deberían tenerse muy en cuenta a la hora de diseñar o modificar las políticas comerciales. Esto es especialmente importante a la luz del posible aumento de las políticas proteccionistas que podrían obstaculizar el funcionamiento de las CGV.

Los responsables políticos deberían estar siempre interesados en comprender cómo mejorar la PTF debido a sus implicaciones para el crecimiento económico. Sin embargo,

es de especial interés para España porque la productividad es uno de los problemas estructurales de la economía española (Fundación BBVA e Ivie, 2019). Por lo tanto, este estudio contribuye a las políticas futuras desentrañando uno de los factores detrás de la disminución de una mala asignación de recursos, lo que puede utilizarse para impulsar la PTF.

Asimismo, las estrategias de internacionalización, pero en particular la participación en las CGV, han suscitado la atención de los países en desarrollo. Dado que representa una valiosa oportunidad para estos países, existe un interés creciente por conocer los factores determinantes y los efectos de la participación en las CGV, especialmente a nivel de empresa. En el Capítulo 3 abordamos esta cuestión para el África Subsahariana. En particular, arrojamos luz sobre los factores que determinan la participación de las empresas en las CGV y los beneficios que pueden obtener al participar en ellas. Para corregir la posible endogeneidad al responder a estas preguntas, aplicamos estrategias de variables instrumentales y una metodología de emparejamiento por propensión ("*propensity score"*).

Los resultados del Capítulo 3 muestran que las buenas infraestructuras, la calidad de las instituciones y la seguridad para prevenir la delincuencia favorecen la participación. Por el contrario, el difícil acceso a la financiación, la existencia de un sector informal o los elevados costes comerciales desalientan la participación. Por otra parte, observamos que las empresas del África Subsahariana que participan en las CGV obtienen mejores resultados en innovación, mayor productividad, pagan salarios más altos y generan más empleo. Esto sugiere que esta participación puede ayudarles a crecer, desarrollarse y desempeñar un papel activo en la escena internacional.

La contribución de este capítulo es múltiple. En primer lugar, ofrece un análisis en profundidad de las CGV en el África Subsahariana desde el punto de vista de las

empresas, mientras que los estudios anteriores utilizan datos agregados a nivel de país o de sector-país sobre las CGV. En segundo lugar, considera conjuntamente los efectos de una serie de variables del entorno empresarial en la decisión de las empresas de participar en las CGV. En tercer lugar, no sólo explica la participación de las empresas en las CGV, sino que también estudia sus efectos en diversas medidas de rendimiento empresarial (mientras que los estudios anteriores se centran en los determinantes o los efectos de la participación en las CGV). Entre ellos se incluyen la innovación, la productividad, los salarios y el empleo de las empresas. En cuarto lugar, utilizamos indicadores de los márgenes extensivo e intensivo de la participación en las CGV, mientras que los trabajos anteriores sólo tienen en cuenta el margen extensivo cuando utilizan datos a nivel de empresa (Antràs, 2020). En quinto lugar, consideramos tanto la integración *backward* (FVA) como *forward* (IVA).

Desde un punto de vista de las políticas públicas, es conveniente remarcar respecto a los determinantes de cara a la entrada en las CGV que, aunque existen varios proyectos multinacionales y regionales de ayuda al comercio en África destinados a reducir las barreras al comercio y las infraestructuras (OECD, WTO, 2015), aún se requieren nuevas políticas complementarias dirigidas a superar las barreras restantes. Por otra parte, la participación en las CGV puede ayudarles a crecer, desarrollarse y desempeñar un papel activo en el escenario internacional. Sin embargo, aún les queda camino por recorrer.

Como contrapunto final del Capítulo, un resultado sobre el que reflexionar es el obtenido para el grado de cualificación de los trabajadores, con un efecto negativo sobre la probabilidad de participar en las CGV. Hasta ahora, los países subsaharianos tienen la ventaja comparativa de estar dotados de abundante mano de obra no cualificada de bajo coste, lo que ha resultado atractivo para las actividades manufactureras intensivas en mano de obra. Sin embargo, como destaca Rodrik (2018), las CGV son cada vez más

intensivas en nuevas tecnologías, lo que puede suponer una amenaza para estos países. La falta de competencias necesarias para manejar estas tecnologías puede disminuir su ventaja comparativa, ya que varios autores destacan la importancia de la mano de obra cualificada (Hollweg, 2019) o incluso la automatización (Stapleton, 2019) en las CGV. Los responsables políticos deberían prestar atención a este riesgo, y es por ello también que en el Capítulo 4 abordamos esta cuestión.

Por tanto, en el Capítulo 4, el último de la tesis, pretendemos profundizar en un debate actual clave en economía internacional: ¿Qué papel desempeñan las nuevas tecnologías en la reciente evolución de las CGV?

Las nuevas tecnologías, como la robótica, una de las principales tecnologías de automatización en la industria manufacturera, pueden facilitar el *reshoring* (Rodrik, 2018). De ahí que este Capítulo pretenda abordar la falta de evidencia científica respecto a la relación entre robotización y *reshoring*. Creemos que la industria manufacturera española es un caso de estudio relevante para este análisis, ya que según el Informe Mundial de la *International Federation of Robotics* (2021), España ocupa el cuarto lugar en instalaciones de robótica industrial en Europa (después de Alemania, Italia y Francia), y el décimo en el ranking mundial. Así, este capítulo investiga el impacto de la adopción de robots por parte de las empresas sobre el *reshoring*, diferenciando entre *reshoring* desde países desarrollados o en desarrollo y examinando si se produce a través de la sustitución de proveedores extranjeros por proveedores nacionales o por producción interna en la empresa. El estudio también analiza el efecto del *reshoring* inducido por la robotización en el empleo de las empresas.

Desde una perspectiva metodológica, nuestro trabajo utiliza una combinación de estimadores de efectos fijos bidireccionales (*TWFE*) y estimadores de diferencias en diferencias (DiD) con adopción escalonada (Callaway y Sant'Anna, 2021). En nuestro

análisis, tratamos la adopción de robots como variable de tratamiento y examinamos sus efectos sobre el *reshoring*. Los resultados sugieren que la adopción de robots conduce al *reshoring*, principalmente desde los países desarrollados, impulsado por la sustitución del abastecimiento en el extranjero por la producción interna a la empresa. Esto respalda una conclusión del Capítulo de que el *reshoring* contribuye a aumentar el empleo en las empresas. Sin embargo, el efecto positivo sobre el empleo disminuye en cierta medida cuando el *reshoring* va acompañado de la adopción de robots, ya que es probable que éstos participen en la producción de una parte de los bienes ahora producidos dentro de la empresa.

Hasta donde sabemos, este capítulo representa el primer análisis exhaustivo que examina los efectos de la adopción de robots en el *reshoring* utilizando datos a nivel de empresa tanto para el uso de robots como para las medidas de *reshoring*. Los estudios anteriores sobre este tema han sido limitados en su alcance, basándose principalmente en datos sectoriales por países y careciendo de un examen detallado de la dinámica a nivel de empresa. Además, estos estudios no diferenciaban entre los orígenes de aprovisionamiento a nivel de empresa ni exploraban si el *reshoring* implicaba la sustitución de proveedores extranjeros por producción interna o por proveedores nacionales. Así pues, este capítulo viene a contribuir sobre una importante laguna en la investigación al realizar un análisis exhaustivo de la relación entre la adopción de robots y el *reshoring*. Además, también da un paso más al examinar el efecto combinado de la robotización y el *reshoring* en el empleo de las empresas. Al investigar la interacción entre estos dos fenómenos, el capítulo ofrece información valiosa sobre cómo configuran conjuntamente el empleo en las empresas. Este enfoque holístico proporciona una comprensión más completa de las complejas interacciones entre la robotización, el

*reshoring* y los resultados en materia de empleo, lo que supone una valiosa contribución al limitado corpus de literatura en este campo.

Por lo tanto, en lo que respecta a las implicaciones políticas, este estudio no confirma que la automatización en un país desarrollado sustituya a los insumos intermedios de los países en desarrollo, sino a los insumos intermedios de otros países desarrollados, y esta sustitución es temporal hasta que los países desarrollados reaccionan. En principio, nuestras conclusiones pueden ofrecer cierto alivio a los países en desarrollo en lo que respecta al impacto de la robotización. Sin embargo, no podemos determinar a partir de este estudio si ello se debe a un ajuste a la baja de sus salarios en respuesta a la pérdida de competitividad. No obstante, si la adopción de la robotización en un país desarrollado incita a otros países desarrollados a seguir su ejemplo y recuperar competitividad, podría dar lugar a una escalada incierta de la robotización. Además, nuestro estudio pone de relieve que el *reshoring* resultante de la robotización en un país desarrollado puede producirse a través de la sustitución de proveedores extranjeros por producción interna en las empresas. Este *reshoring* puede contribuir al empleo dentro de la empresa y desempeña un papel fundamental en el actual debate sobre la disyuntiva entre robotización y empleo.

En resumen, esta tesis presenta un estudio exhaustivo de la internacionalización, y especialmente de las CGV, desde el punto de vista de las empresas. Explora sus beneficios para España, incluyendo la mitigación de la destrucción de empleo y la reducción de la *misallocation* de recursos, así como sus impactos positivos en los países en desarrollo, como el aumento del empleo, la innovación y los salarios. A continuación, se centra en el actual debate sobre el papel de los robots en las actividades de *reshoring*. Aquí pretendemos arrojar luz sobre si estas nuevas tecnologías están impulsando el *reshoring* desde países desarrollados o en desarrollo y si se produce mediante la sustitución de

proveedores extranjeros por proveedores nacionales o mediante la producción interna en la empresa.

El resto de la Tesis se organiza de la siguiente manera: Capítulo 1 bajo el título "*The Export Strategy and SMEs Employment Resilience During Slump Periods* ". Capítulo 2 titulado "*Misallocation of intermediate inputs and Global Value Chains* ". Capítulo 3 bajo el título: "*How do firms in Sub-Saharan Africa benefit from Global Value Chains?*". Capítulo 4 con el título: "*Robots and firm reshoring*". Finalmente, la última sección presenta las conclusiones y las implicaciones políticas.

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# Introduction

This doctoral thesis presents an in-depth analysis of internationalisation strategies with special emphasis on participation in Global Value Chains (GVCs). This way, the main objective of the thesis is to present a comprehensive study of internationalisation and GVCs from a firm-level perspective. To do this, we firstly examine how internationalisation strategies can affect firm performance. And subsequently, we delve into the discussion on the recent trends of globalisation, analysing the connection between the expansion of new technologies and reshoring strategies.

Particularly, in the first three chapters, we explore how internationalisation, especially in the context of GVCs, may contribute to firm performance. Firstly, we begin by addressing one of the main challenges for an economy, namely, unemployment, an issue that becomes more pronounced during times of crisis. Thus, Chapter 1 investigates the moderating role of exports in job destruction associated with recessive contexts of domestic demand, using Spain and Spanish manufacturing SMEs as a case study.[2] Secondly, in Chapter 2, another issue of special interest is addressed. In this case, one that impedes Total Factor Productivity (TFP) growth and aggregate output growth: misallocation of production factors. Therefore, this Chapter examines whether GVC engagement may help alleviate firms' misallocation of intermediate inputs. Additionally, we test this hypothesis specifically for Spanish manufacturing firms.

Thirdly, Chapter 3 considers that GVCs represent an opportunity for developing countries to enter global markets (Kowalski et al., 2015; Stamm, 2004). They can join

[2] This Chapter has been published as Aparicio-Pérez, D., Calatayud, C., & Rochina-Barrachina, M. E. (2021). The Export Strategy and SMEs Employment Resilience During Slump Periods. *Economics*, *15(1),* 163-186.

them and save decades of investment in forming their own supply chains (Baldwin, 2013). Specially, African countries have been particularly dynamic in recent years, with trade growth outpacing that of most economies. However, Sub-Saharan Africa remains the least integrated region in the world. Therefore, this chapter identifies the determinants and effects of GVC participation by manufacturing firms in the region.[3]

Finally, for the last Chapter, we acknowledge the recent trends of globalisation and the current debate regarding "slowbalisation" of trade and value chains. Hence, given that new technologies may facilitate reshoring (Rodrik, 2018), we examine how the growing utilisation of robots (the main automation technology in manufacturing) has contributed to the current trend of Global Value Chains. We believe that the Spanish manufacturing industry is a relevant case study for this analysis, as according to the International Federation of Robotics' World Report (2021), Spain ranks fourth in industrial robotics installations in Europe (after Germany, Italy and France), and tenth in the world ranking. It has a robot density of more than 200 robots per 10,000 workers, significantly higher than the world average.

All along the thesis, we will use firm-level data. Internationalisation is ultimately a firm strategy, and specially for GVC participation there is a growing interest in studies that capture it at this decision level. Moreover, using this type of data helps overcome problems arising from the use of more aggregated data, such as insufficient variability in regression analysis, presence of aggregation biases or the imputation of some data in some countries' input-output tables.

[3] This Chapter has been published as Calatayud, C. & Rochina Barrachina, M.E. (2023). How do firms in Sub-Saharan Africa benefit from global value chains? *South African Journal of Economics, 91(2),* 214–241.

In Chapters 1, 2, and 4, which specifically focus on Spain, we use a firm-level panel dataset obtained from the Spanish Survey of Business Strategies (ESEE). The ESEE is an annual survey, sponsored by the Spanish Ministry of Industry and conducted by the SEPI Foundation, which is representative (by industry and size) of the manufacturing sector in Spain. For Chapter 3 we use rich firm-level data from the World Bank Enterprise Survey for manufacturing sectors in 18 Sub-Saharan African countries.

Studying internationalisation strategies for Spain is particularly appealing. First of all, from the crisis of 2008, there was a spectacular growth in exports that has been coined as the "Spanish miracle" (Eppinger et al., 2017). Moreover, regarding the trade of intermediates, which is directly related to GVCs (Antràs, 2020), Spain ranks among the top 10 EU countries in terms of imports of intermediate products. In fact, these imports of intermediate products have nearly doubled since 2000 (European Commission, 2022). Hence, studying how these trade activities affect firms is of interest.

Specifically, Chapter 1 focuses on the significant increase in exports experienced in Spain since 2008, especially for SMEs. This is noteworthy because during the same period, the Spanish economy was severely impacted by the Great Recession, leading to a pronounced decrease in Gross Domestic Product (GDP) and a significant impact on internal demand. Furthermore, this economic downturn led to a substantial increase in unemployment. Hence, with this scenario, our main objective is to investigate the moderating role of exports in job destruction associated with recessive contexts of domestic demand using Spanish manufacturing SMEs as a case study.

To tackle this issue, we first estimate an export equation, in which we analyse whether the "venting out"[4] hypothesis holds, and thereby helps us to explain the

[4] "Venting out" hypothesis is the substitutability of domestic demand by exports.

aforementioned moderating effect. Moreover, we check whether the prediction in Almunia et al. (2021), whereby the firms with the highest production capacity used are the ones that react most strongly to a drop in internal demand, becoming exporters, holds. To do this, we include pre-sample means of the dependent variable in the estimation equation to deal with correlated unobserved individual heterogeneity and we implement a Heckman's (1979) two-stage selection correction to correct for non-random attrition due to observability of SMEs export decisions only for firms continuing in operation. Secondly, to answer the main question of the Chapter, we estimate a dynamic employment equation.

We obtain that exporting SMEs show greater resilience in terms of employment in a period of recession than non-exporting SMEs. Furthermore, this compensatory effect of exports on employment works in favor of permanent workers, being statistically insignificant for temporary workers. This implies that the ratio of permanent to temporary workers increases for SMEs during recessive periods. In addition, exporting increases SMEs survival chances. Finally, we provide further evidence supporting that SMEs participation in exports also obeys to a reaction to the fall in domestic demand (the so-called "venting out" hypothesis). Likewise, we confirm the theoretical prediction in Almunia et al. (2021), which states that firms with a higher production capacity used can benefit the most by adapting in the short term to the fall in domestic demand.

We consider that the main contributions of our work are the following. First, it provides new evidence to the literature exploring at the firm level the effects of exports on employment. Second, it helps to understand the role of firms' export decisions in mitigating unemployment when a domestic recession hits the economy. Third, it focuses especially on SMEs, the most vulnerable group of firms in a crisis. Fourth, it delves into the compositional effects on employment in relation to the different types of contracts

(permanent and temporary), in order to eventually offer policy recommendations not only on how to mitigate the drop in employment after a shock but also on how to improve its quality in terms of the duration of contracts. Finally, and regarding the hypothesis of "venting out" already tested in some previous works, a step forward has been taken and the prediction related to firms' capacity utilization in the theoretical model of Almunia et al. (2021) has been directly tested.

Next, Chapter 2 delves deeper into GVCs in Spain and explores the role they may play in mitigating misallocation of production factors. First of all, misallocation of production factors occurs when available resources are inefficiently distributed among firms. This inefficiency hinders aggregate output growth. Since it results from the reallocation of production factors without varying the input amount, it has direct implications for TFP growth. Therefore, the study of factor misallocation is relevant not only due to its implications for aggregate output but also for TFP growth.

Particularly, our working hypothesis posits that increased participation in GVCs might be a key factor contributing to a more efficient allocation of intermediate inputs. To the best of our knowledge, this particular aspect remains unexplored in the existing literature. GVCs are intricately linked with trade of intermediate goods (Antràs, 2020). Consequently, firms engaged in GVCs enjoy distinct advantages when it comes to accessing intermediate inputs (Halpern et al., 2015; Máñez et al., 2020; Máñez Castillejo et al., 2020). Unlike those reliant solely on domestic sourcing, these firms are not constrained by geographical boundaries, affording them greater flexibility in adapting to market frictions that may arise in specific markets.

We conduct this analysis for Spain, as its economy witnessed an improvement in aggregate productivity levels since 2009, accompanied by an increased participation in Global Value Chains (GVCs) and a reduction in misallocation of intermediate inputs.

To study the link between GVCs and intermediates misallocation, we apply Petrin and Sivadasan (2013)'s methodology to study misallocation from a firm-level point of view. They propose to calculate a "gap", where they use production data to estimate the differences between the value of the marginal product of an input and its marginal cost. Moreover, we build two main indicators of GVCs identifying the extensive and intensive margin of participation in GVCs. These are the Foreign Value Added (FVA), which identifies the content of intermediate imports embodied in exports, and the Indirect Value Added (IVA), that represents the domestic value added in inputs sent to third economies for further processing and export through value chains.

Then, we start by applying Ordinary Least Squares (OLS) and Two-way Fixed Effects (TWFE) estimators to see the relationship between GVC engagement and intermediates misallocation. However, we acknowledge the limitations of these estimation methods, and thus we exploit the variation in treatment times, as firms may be treated at different times. That is to say, firms engage in GVCs at different points in time. In order to do so, we rely on Callaway and Sant'Anna's (2021) setup and implement a Difference-in-Differences (DiD) estimator with staggered adoption. Furthermore, we apply a DiD approach with continuous treatment intensity, exploiting the emergence and expansion of fibre-optic-based ICT technology facilitating GVC operations. With all these methods, we corroborate our hypothesis. This is, we find that participation in GVCs helps alleviate intermediates misallocation.

We contribute to the literature on the study of misallocation adding several novelties. First, in this chapter we focus on the study of the misallocation of intermediate inputs, while previous papers focused on capital or labour. This way, we are able to unravel a factor that helps reduce intermediates misallocation: the engagement in GVCs. Second, with respect to previous studies on this topic for the Spanish economy, we

broaden the temporal scope of the analysis, as other papers focused mainly on misallocation in the period prior to the Great Recession. Third, and in contrast to the work for Spain and most of the work for other countries, we conducted the analysis from a firm-level perspective, while other papers had a more aggregated viewpoint. Finally, our database allows us to use firm-level output and input deflators, while other papers use industry deflators, which may introduce a bias in the estimates of intermediate input elasticities in the production function.

Likewise, the internationalisation strategies, but particularly GVC engagement, has arisen attention for developing countries. As it represents a valuable opportunity for these countries, there is a growing interest in knowing the determinants and effects of GVC participation, specially at the firm level. In Chapter 3 we tackle this issue for Sub-Saharan Africa. Particularly, we shed light on what factors determine firms' participation in GVC and the benefits they can retrieve by engaging in them. To correct for potential endogeneity when answering these questions, we implement Instrumental Variables strategies and a propensity score methodology.

The results in Chapter 3 show that good infrastructure, quality of institutions and security to prevent crime favour participation. In contrast, difficult access to finance, the existence of an informal sector or high trade costs discourage participation. On the other hand, we find that Sub-Saharan African firms participating in GVCs enjoy superior innovation performance, higher productivity, pay higher wages and generate more employment. This suggests that this engagement can help them grow, develop and play an active role in the international arena.

The contribution of this Chapter is manifold. First, it provides an in-depth analysis of GVCs in Sub-Saharan Africa from the point of view of firms, whereas previous studies use aggregate country or sector-country-level data on GVCs. Second, it jointly considers

the effects of a battery of business environment variables on firms' decisions to participate in GVCs. Third, it not only explains firms' participation in GVCs but also studies its effects on various measures of firm performance (whereas previous studies focus on either the determinants or the effects of GVC participation). These include innovation, productivity, wages and employment of firms. Fourth, we use indicators of the extensive and intensive margins of GVC participation, whereas previous work only considers the extensive margin when using firm-level data (Antràs, 2020). Fifth, we consider both backward (FVA) and forward (IVA) integration.

Finally, in Chapter 4, the last chapter of the thesis, we aim to delve into a key current debate in international economics: What role do new technologies play in the recent trend of GVCs?

New technologies such as robotics, one of the main automation technologies in manufacturing, may facilitate reshoring (Rodrik, 2018). Hence, this Chapter aims to address the lack of scientific evidence regarding the relationship between robotisation and reshoring. We believe that the Spanish manufacturing industry is a relevant case study for this analysis, as according to the International Federation of Robotics' World Report (2021), Spain ranks fourth in industrial robotics installations in Europe (after Germany, Italy and France), and tenth in the world ranking. Thus, this Chapter investigates the impact of firms' adoption of robots on reshoring, differentiating between reshoring from developed or developing countries and examining whether it occurs through the substitution of foreign suppliers with domestic suppliers or by internal production within the firm. The study also analyses the effect of robotisation-induced reshoring on firms' employment.

From a methodological perspective, our chapter utilises a combination of TWFE estimators and DiD estimators with staggered adoption (Callaway and Sant'Anna, 2021).

In our analysis, we treat robot adoption as the treatment variable and examine its effects on reshoring. The findings suggest that the adoption of robots leads to reshoring, primarily from developed countries, driven by the substitution of foreign sourcing with internal production within the firm. This supports the finding of the chapter that reshoring contributes to increase firm employment. However, the positive effect on employment is somewhat diminished when reshoring is accompanied by robot adoption, as robots are likely involved in the production of a portion of the reshored goods within the firm.

To the best of our knowledge, this Chapter represents the first comprehensive analysis that examines the effects of robot adoption on reshoring using firm-level data for both robot use and reshoring measures. Previous studies on this topic have been limited in their scope, mainly relying on country-sector data and lacking a detailed examination of the firm-level dynamics. Additionally, these studies did not differentiate between the sourcing origins at the firm level nor explore whether reshoring involved the substitution of foreign suppliers through in-house production or domestic suppliers. Thus, this Chapter fills a significant research gap by conducting a thorough analysis of the relationship between robot adoption and reshoring. In addition, it also goes a step further by examining the combined effect of robotisation and reshoring on firms' employment. By investigating the interplay between these two phenomena, the Chapter offers valuable insights into how they jointly shape employment within firms. This holistic approach provides a more comprehensive understanding of the complex interactions between robotisation, reshoring, and employment outcomes, making a valuable contribution to the limited body of literature in this field.

In a nutshell, this thesis presents a comprehensive study of internationalisation, and especially GVCs, from a firm-level point of view. It explores the benefits of them for Spain, including the mitigation of job destruction and reduction of misallocation, as well

as their positive impacts on developing countries, such as increased employment, innovation, productivity and wages. Next, it centres on the ongoing debate concerning the role of robots in reshoring activities. Here, we aim to shed light on whether these new technologies are prompting reshoring from developed or developing countries and whether it occurs through substitution of foreign suppliers with domestic suppliers or by firms' internal production.

The remaining of the Thesis is organised as follows: Chapter 1 under the title "The Export Strategy and SMEs Employment Resilience During Slump Periods". Chapter 2 entitled "Misallocation of intermediate inputs and Global Value Chains". Chapter 3 titled "How do firms in Sub-Saharan Africa benefit from Global Value Chains?". Chapter 4 under the title: "Robots and Firm Reshoring". Finally, the last section presents the conclusions and policy implications.

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# Chapter 1. The export strategy and SMEs employment resilience during slump periods

## 1.1. Introduction

Our main research question in this chapter is whether, for SMEs, exporting helps to mitigate job losses in periods of recession especially characterised by a slump in domestic demand. Thus, the main objective of this section is to motivate our study and shed light on the relationships of the mentioned variables.

When a crisis arrives, there may be multiple consequences in the economic, political or social fields, but they differ across countries and firms. Focusing on the latter, recessions have been considered a time when the most unproductive firms are forced to exit, what is known as the cleansing effect of recessions (Caballero and Hammour, 1994; Osotimehin and Pappadà, 2017). Therefore, not all firms are affected in the same way when a recession comes.

More precisely, firms' size is one characteristic that specially affects the behaviour of firms when bad times arrive. That is to say, SMEs tend to suffer more during these times. In first place, they are much more sensitive to the business cycle or other market frictions (Beck et al.,2008; Bakhtiari et al., 2020; Crouzet & Mehrotra, 2020), and, in a second place, recession periods can be especially harmful for them since they tend to be also less efficient than their bigger counterparts, leading to less chances of survival (Bartoloni et al., 2020; Melitz, 2003). Additionally, boom periods such as those before the Great Recession appear to be characterised by misallocation of capital, that is, capital may have been too directed towards unproductive firms (Cette et al. 2016), which may have helped to the survival of relatively inefficient firms during pre-recessive periods. In this line, Gopinath et al. (2017) showed for Spain that such capital distortions have

contributed to the survival of small and relatively inefficient firms. This was also confirmed for Portugal by Dias et al. (2014). Consequently, when a recession arrives, there may be a reallocation of capital to the most productive firms, which can lead to the death of the most inefficient ones.

Likewise, the crisis period not only goes hand in hand with the exit of firms, but also with the rise of unemployment, where it is especially noteworthy the case of the Great Recession. However, this increase in unemployment was again not equally distributed. Workers in small firms were more likely to become unemployed during the 2007–2009 recession than comparable workers in large firms (Duygan-Bump et al., 2015). Nevertheless, this effect on employment for SMEs is not casual. The poorer financial conditions they face are one of the drivers of this negative impact on employment. It has been largely documented that SMEs face tighter resource constraints than large businesses, becoming particularly tough when financial markets are volatile and unfavorable, as it happened during the crisis of 2008 (Bakhtiari et al., 2020). Hence, these impacts, among others, firm's survival and employment. Indeed, in times where SMEs experience a negative demand shock, credit constraints play a detrimental role on employment among this type of businesses (Cornille et al., 2019; Westergaard-Nielsen and Neamtu, 2012; Campello et al., 2010). Besides, SMEs may have relied particularly on the layoff of temporary employees in order to carry out the job adjustment (Cornille et al., 2019).

Therefore, an important question for SMEs is what makes them more resilient to recessions? What characteristics help them overcome the negative impact of bad times on issues like firms' employment? In the literature, some works point out that operating in a market with lower competition reduces the risk of being affected by a crisis (Westergaard-Nielsen and Neamtu, 2012), while others affirm that firms with a superior enterprise risk

management capability can cope better with downturns (Nair et al., 2014). More particularly, although SMEs are expected to suffer the most during the crisis as discussed above, they also tend to be more flexible and more open to opportunities (Eggers, 2020). In this line, some authors have highlighted that one key factor to proactively react to a recession is the SMEs' engagement in foreign trade (Geroski and Gregg, 1997; Máñez et al., 2022). In a general way, exporters are expected to perform better in terms of employment, chances of survival and sales growth in comparison with non-exporters when facing a crisis (Görg and Spaliara, 2014), being the smallest firms the most benefited by export promotion activities (Munch and Schaur, 2018). In this way, new seminal works have pointed out this strategic decision of exporting as a way to deal with recessions in a context of an important drop in domestic demand, the so-called "venting out" hypothesis (Almunia et al., 2021).

Several papers in the literature have investigated the role of exports on employment, identifying a positive impact. At an industry level, Feenstra et al. (2019) found that export job creation offsets the import job destruction in the United States, while Kiyota (2016) showed that in China, Indonesia, Japan, and Korea exports can create employment, although this effect is not limited to the export-industries but it may have an impact on industries that are not particularly export-oriented through vertical inter-industry linkages. Likewise, with regards to the relationship between exports and unemployment, the literature has used aggregate data to find that the former can help reduce the latter. Dritsakis and Stamatiou (2018) showed that, for European countries, exports are not only important when it comes to promoting economic growth, but also to reduce unemployment. The same result is found for developing countries such as Malaysia (Subramaniam, 2008). Moreover, it has been even established that after World War II, the

boom in exports in the US played a strong and key role to prevent a significant rise in unemployment (Taylor et al., 2011).

On the other hand, at a firm level, Bernard and Jensen (1999) showed that in the US, exporting not only increases the probability of survival, but also leads to higher employment growth on any horizon. More recently, but also along this line, Lo Turco and Maggioni (2013) found evidence of a positive impact of firms' internationalisation activities on firms' employment in Turkey, whilst Biscourp and Kramarz (2007) showed a positive relationship between exports and employment growth in France. Likewise, using Danish firm-level data, Munch and Schaur (2018) found that export promotion leads to an increase of 4 percentage points on employment. Finally, Capuano and Schmerer (2015) found a negative relationship between trade and unemployment in Germany, indicating that trade liberalisation helps reduce unemployment in the long run.

Hence, it seems from previous studies that exports have a positive impact on employment, being a factor that helps mitigate the problem of unemployment. This leads us to the following question: what factors facilitate or discourage firms to export? One that we cannot ignore is the presence of financial restrictions, as it influences trade and internationalisation strategies. For instance, financial constraints have been shown to be critical when engaging in FDI (Gil-Pareja et al., 2013; Buch et al., 2014). Moreover, in the same way, financial constraints of domestic firms have a deterrent effect not only on their probability to export but also on their export intensity (Kim, 2019). Besides, for SMEs in particular, Máñez and Vicente-Chirivella (2021) found that, using a financial score to measure the degree of financial constraints, SMEs with better financial health are more likely to export. Equally, they showed that financial health is positively associated with export persistence. This is another argument that supports that SMEs are very likely to be the most affected as a result of a recession, since they tend to have more financial

constraints and are more likely to disappear and suffer an adverse effect on employment. This is coupled with the fact that SMEs are especially relevant in Europe since they account for 99% of all businesses in the EU and provide two out of three jobs in the private sector (Interreg Europe, 2021). Although they account for fewer resources because of its size, they have proven to be flexible actors with a certain capacity to deal with turbulent times. Nevertheless, as stated at the beginning, the consequences of the Great Recession differ not only between firms of different sizes but also between countries. In relation to this, it must be said that the 2008 financial crisis particularly affected southern Europe (Zamora-Kapoor and Coller, 2014). But more precisely, the most interesting case for this work is Spain, since it was the only country in the EU that suffered a sharp drop in GDP, a record rise in unemployment rates, but at the same time experienced an incredible take-off in its export participation, especially for SMEs.

In addition to financial restrictions, there are two more relevant variables to explain the decision to export of SMEs. First, in a Melitz (2003) type model of trade, the decision to export is a function of productivity, and are precisely the most productive firms the ones that export. Second, the incentives to export if the aforementioned "venting out" hypothesis (Almunia et al., 2021) is met. The model in their paper establishes a theoretical causal link between a fall in domestic demand and an increase in firms' incentives to export (more details on this will be provided at the beginning of section 1.4 in this chapter). Furthermore, their model also predicts that this substitution between internal and external demand should be stronger for firms with greater use of their productive capacity.

Having said all this, once firms export our main objective in this work is to investigate the role of export participation as a means for Spanish manufacturing SMEs to maintain employment in recessive periods in which domestic demand is depressed and

external markets can pull employment. Exporting SMEs can begin to use their productive capacity released in the short term due to the fall in domestic demand and hire workers to respond to the increase in external demand. Furthermore, we also want to find out whether the effect of exports on SMEs employment affects the composition of their workforce in terms of permanent *versus* temporary contracts. Finally, the theoretical framework in section 1.4 will reveal in detail why it is also relevant for us to explain what lies behind the SMEs decision to export. At this stage, we will pay special attention to supply and demand factors (including access to finance).

To anticipate the main results in this chapter, we obtain that exporter SMEs not only have a higher level of employment than non-exporters, but they can also offset part of the employment losses that are generated during a recessionary period that mainly affects domestic demand. This compensation acts in favour of permanent workers, meaning that the ratio of permanent to temporary workers increases during these recessive periods. Thus, exporting SMEs show greater resilience in terms of employment when affected by a recession than non-exporters. In addition, SMEs use the export strategy as a means to avoid death and overcome periods of downturn in their domestic sales. In relation to this last point, we throw new empirical evidence on the "venting out" hypothesis (de Lucio et al., 2019; Máñez et al., 2022; Almunia et al., 2021). Finally, but very importantly, we also confirm the theoretical prediction in Almunia et al. (2021): those firms with the highest capacity utilization have the greatest incentives to export when domestic demand falls.

We consider that the main contributions of our work are the following. First, it provides new evidence to the literature exploring at the firm level the effects of exports on employment. Second, it helps to understand the role of firms' export decisions in mitigating unemployment when a domestic recession hits the economy. Third, it focuses especially on SMEs, the most vulnerable group of firms in a crisis. Fourth, it delves into

the compositional effects on employment in relation to the different types of contracts (permanent and temporary), in order to eventually offer policy recommendations not only on how to mitigate the drop in employment after a shock but also on how to improve its quality in terms of the duration of contracts. Finally, and regarding the hypothesis of "venting out" already tested in some previous works, a step forward has been taken and the prediction related to firms' capacity utilization in the theoretical model of Almunia et al. (2021) has been directly tested. This has been possible because the database used for this work has information on the percentage in which the firm uses its productive capacity. To our knowledge, this is the only work we are aware of that addresses all of these issues simultaneously and within a unified theoretical framework based on the work of Almunia et al. (2021), fundamental to our analysis. This has been a challenge for us, since their work is focused on explaining firms' export decisions and in its empirical part it does not include employment equations as a dependent variable nor does it distinguish between temporary and permanent work in those equations. However, its theoretical model and its empirical application is rich and interesting enough to inspire our work.

The remainder of the chapter is organised as follows. In section 1.2, we show why the Spanish case has been chosen as a relevant case study to investigate the moderating role of exports in employment destruction associated with recessive contexts, especially characterised by the poor performance of domestic demand. Section 1.3 describes the database used in this work. Section 1.4 reports our theoretical framework and estimation results. Finally, section 1.5 concludes.

## 1.2. The Spanish case

As commented in the Introduction, the effects of a crisis differ from one country to another. In this way, the Great Recession that started by late 2007 was an economic downturn that was global in nature but hit sharply countries in Southern Europe (Goldstein et al., 2013; Zamora-Kapoor and Coller, 2014). In Figure 1.1, we provide evidence of the severity of this crisis by showing the evolution of Gross Domestic Product (GDP) for economies in Southern Europe (namely Portugal, Spain, Italy and Greece) as well as for France, Germany and the whole euro area along the period of analysis in this chapter, 2000-2014.[5]

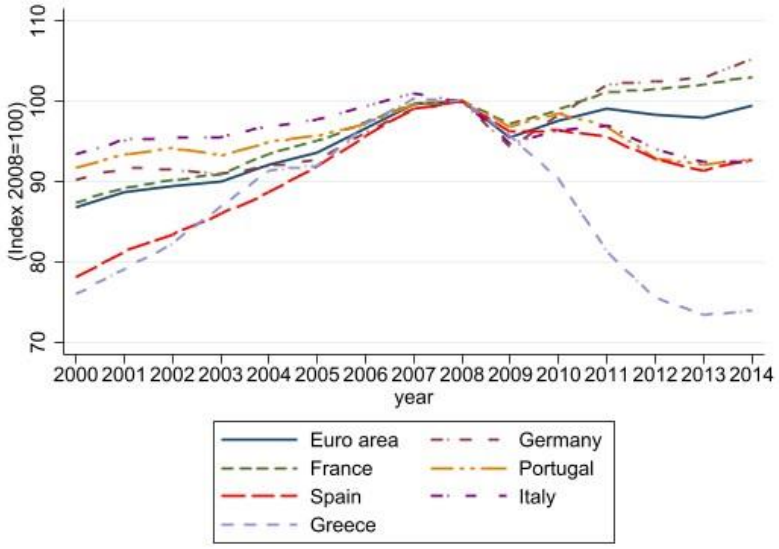
Until 2008 all countries saw how their GDP grew substantially, experiencing the so-called boom years. Nevertheless, in the ongoing years the GDP fell in all cases, heading the economies towards a recession. However, what is remarkable is that only the southern economies were unable to recover their precrisis levels. In 2014, the French GDP had grown by 3.07% in comparison with 2008, the German GDP was 5.26% larger and the GDP for the whole euro area was practically the same as in 2008. But in the case of the Southern European countries the situation was completely the opposite. Neither Spain nor Italy, Portugal or Greece were able to recover from the crisis after 6 years.

Nonetheless, the financial crisis of 2008 had also a severe effect on the labour market, rising the unemployment rates in all countries as it can be seen in Figure 1.2. Before the crisis, all economies presented relatively low unemployment rates, being all below 10%. However, the crisis entailed a shock in the labour market for all economies,

[5] We show together with the southern countries, the evolution of France and Germany since they are considered two major economies in Europe, and the euro area since it is the natural area of reference.
The data has been retrieved from the AMECO database, European Commission (https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/macro-economic-database-ameco/ameco-database_en)

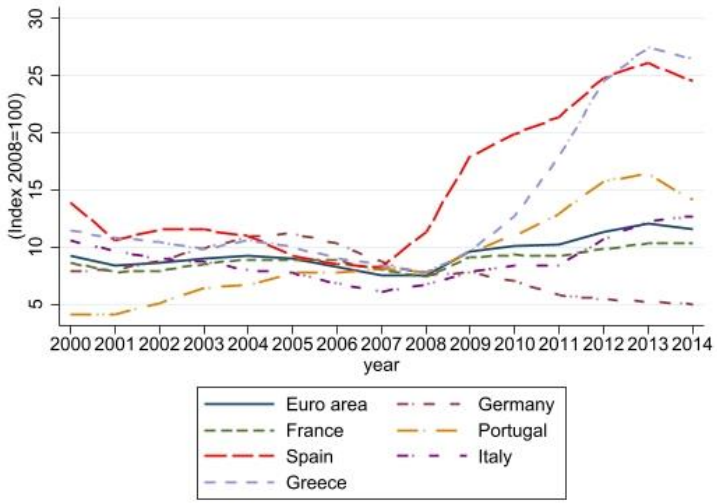
but its magnitude and impact differed widely across countries. In 2014, the scenarios for the different economies were very diverse. The best evolution took place in Germany, which was able to reduce its unemployment rate by 2.5 percentage points in comparison to the precrisis level. On the contrary, the euro area and France suffered a moderate increase, since the unemployment rate rose by 4 and 3 percentage points, respectively. A worse scenario was present in Italy and Portugal, where the unemployment rates doubled. But, in any case, the most worrying rates were in Greece and Spain, where they arrived to surpass the 25%.

Figure 1.1. Evolution of Gross Domestic Product (GDP).




Source: Data from AMECO-EU.

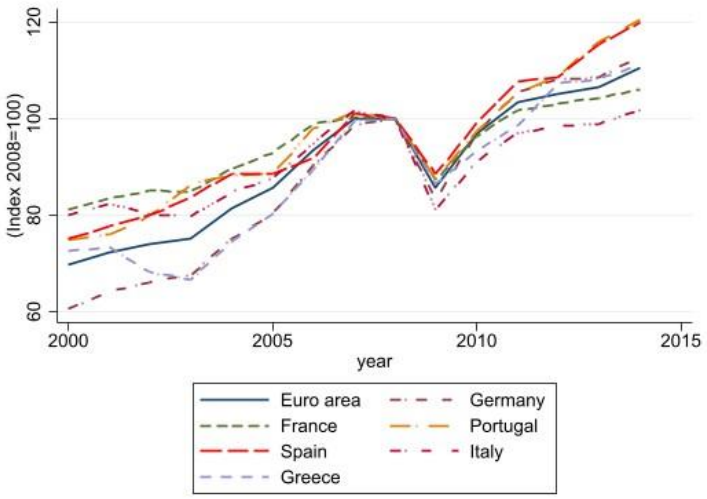
Figure 1.2. Evolution of unemployment rates.




Source: AMECO-EU.

Given this scenario, firms needed to adapt to these conditions, but as explained in the Introduction, when it comes to a recession they could react differently. The engagement in foreign trade has been pointed out as one of the key factors to deal with recessions. Thus, it is interesting to see how exports have evolved during the boom and slump periods for the different economies mentioned above, so Figure 1.3 shows this evolution.

Figure 1.3. Evolution of exports.




Source: AMECO-EU.

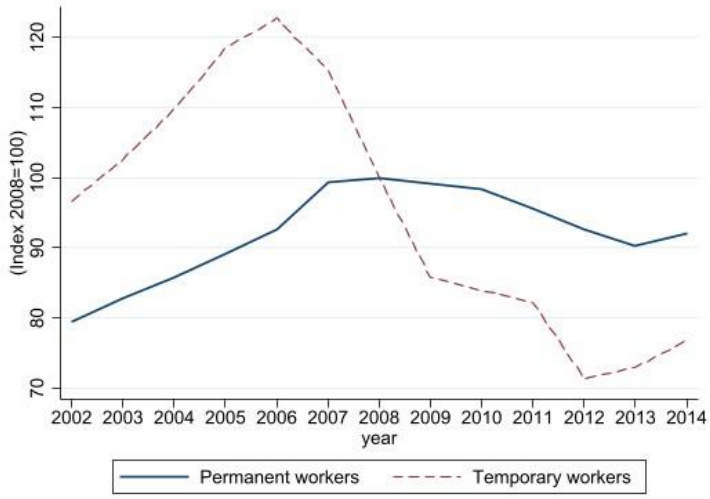
Exports were experiencing a positive trend until the crisis arrived. After 2008 they shrunk, but countries were able to recover the growing path rapidly. However, this growth was not equal for all economies. Italy arrived virtually to the precrisis level in 2014, and France only experienced a 6% growth. Germany and Greece managed to rise their exports by a 10% approximately, in line with the euro area. However, the outstanding increase took place in Spain and Portugal, where exports grew a 20% in comparison to 2008.

Hence, the only country hit severely by the crisis with a sharp fall in GDP, a high increase in the unemployment rate but with an important take off of its exports was Spain. Thus, this makes this southern economy an interesting country to analyse these phenomena and to study whether this increase in exports helped offset the problem of unemployment.

Unemployment has been pointed out as one of the most severe problems in Spain (Furió and Alonso, 2015). As shown in Figure 1.2, there was a general rise in unemployment rates in Europe, but the problem in Spain is more serious since it is structural and systematic. Several papers have analysed deeper this Spanish problem, trying as well to identify the potential solutions (Royo, 2009; Verick, 2009). However, what is also noteworthy for Spain is the employment structure, which is characterised by a high number of temporary workers, traditionally associated with a higher degree of vulnerability and precariousness (López and Malo, 2015). To show this, Figure 1.4 shows how the two different types of workers, permanent and temporary, were affected by the rise in unemployment after the crisis started. [6]

[6] The data has been retrieved from the "Instituto Nacional de Estadística" (https://www.ine.es/jaxiT3/Tabla.htm?t=3961&L=0). Data was only available from 2002. The data of each year corresponds to the fourth quarter of the corresponding year.

Figure 1.4. Permanent and Temporary workers in Spain.



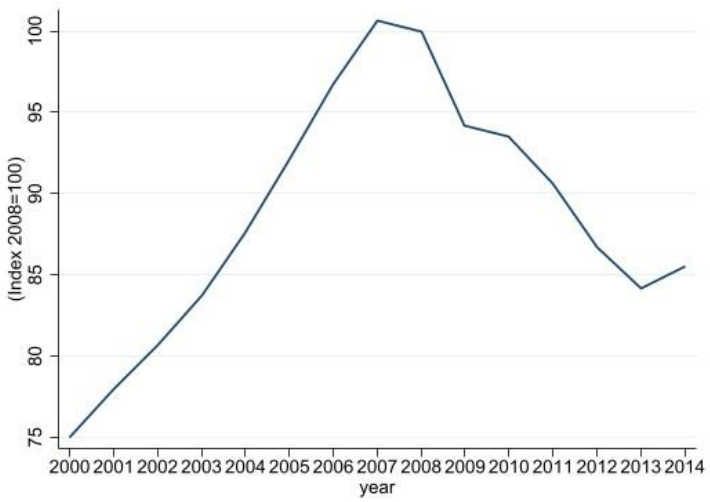

Source: Instituto Nacional de Estadística (INE).

As it can be seen, the evolution of temporary workers is more volatile. While the growth of this type of workers was notable before the crisis, being higher than the growth of permanent workers, it decreased considerably when the recession arrived. As a matter of fact, it fell by a 50% from 2006 to 2012, whilst the number of permanent workers was virtually the same. The intuition for this is that when a firm needs to face a crisis, it is easier to fire temporary workers, since the firing costs for the permanent ones could become a high burden for the firm. This implies a huge flow of temporary workers entering and going out of unemployment (Bentolila et al., 2012). Thus, this reinforces the idea that it is not only interesting to analyse the link between exports and employment, but also to differentiate between workers under the two types of contracts.

Additionally, the spectacular growth in exports in Spain has been coined as the "Spanish miracle" (Eppinger et al., 2017), for which two possible explanations have been proposed. On the one hand, an increase in competitiveness due to supply-side factors, and, on the other hand, the so-called "venting out" hypothesis. The latter attributes the increase in exports (in their extensive and intensive margins) to a strategic response made

by firms to face the fall in internal demand (Almunia et al., 2021). Thus, Figure 1.5 shows the evolution of internal demand in Spain in order to see which was the impact when the recession came.

Figure 1.5. Evolution of Internal Demand in Spain.




Source: AMECO-EU

As it can be seen, the internal demand was experiencing a positive trend before 2007, but it changed its path when the crisis arrived, being a 15% lower in comparison with the precrisis level. Thus, the "venting out" hypothesis may be a potential explanation for the increase in exports in Spain during the slowdown, as it was shown in other papers (de Lucio et al., 2019; Máñez et al., 2022; Almunia et al., 2021).

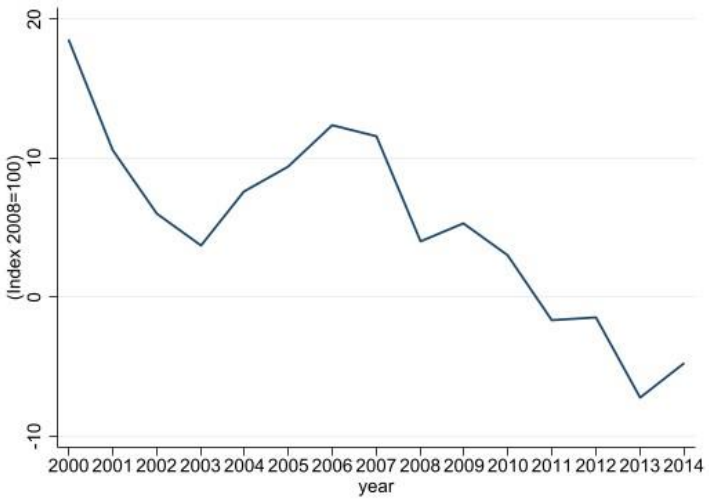
However, as discussed in the Introduction, when it comes to a recession as the one we are dealing with, it is particularly important the fact that financial constraints may become an important obstacle for firm performance. We plot in Figure 1.6 the evolution of loans to nonfinancial institutions, so we can see how they fell when the crisis arrived.

Actually, the rate of growth of credit to nonfinancial institutions became negative in 2011, not being able to recover in 2014. This confirms the increase in financial

restrictions, so we cannot forget this phenomenon in our study, since it was a reality that became a problem for firms in the Spanish economy.

Therefore, as has been made clear in this section, Spain is especially suitable and relevant to study whether exports may help offset unemployment in a context of depressed internal demand and increasing financial restrictions, in a labour market characterised by a strong duality between permanent and temporary workers.

Figure 1.6. Yearly growth of credit to nonfinancial institutions.




Source: Bank for International Settlements[7]

## 1.3. Database and descriptives

In this study, we use a firm-level panel data set obtained from the Spanish Survey on Business Strategies (ESEE) for the period 2000-2014. The selected period allows considering both the boom phase (2000-08), and the slump period that occurred after 2008. The ESEE is a yearly survey, carried out by the SEPI Foundation, which is

[7] Data comes from Bank for International Settlements, Total Credit to Non-Financial Corporations, Adjusted for Breaks, for Spain [QESNAM770A], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/QESNAM770A, August 26, 2021.

representative (by industry and size) of the manufacturing sector in Spain. Firms are classified into 20 different sectors following the NACE-CLIO two-digit classification.

The sampling design of the ESEE is as follows. No firms with employees below 10 are included in the survey. Firms with 10-200 employees (SMEs) are randomly included, being about 5% of the population of firms within this size range in 1990. All firms bigger than 200 workers (large firms) are invited to contribute to the survey, with a participation of about 70% in 1990. To minimise attrition in the initial sample, important efforts have been conducted. Thus, annually new firms are incorporated with the same criterion of the base year to preserve the sample representativeness across time.[8]

In our work, as explained in the Introduction, we focus on SMEs, since, among other things, large firms tend to have fewer financial constraints and are less sensitive to demand conditions.[9] In addition to excluding large firms, we drop out all firms' observations that do not provide information on the relevant variables used in our analysis. Therefore, after cleansing those observations, we have a main working sample of 18,286 observations that correspond to 2,723 firms.

However, to reinforce the idea that SMEs and large firms and exporter and non-exporters behave differently, we show in Table 1.1 some descriptive statistics regarding the main variables we will use in our chapter. Table A1.1 in Appendix 1 contains a detailed description of the variables used.

[8] See https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp for more details.
[9] For the period of analysis, we had 26,926 observations, but dropping large firms, we ended up with 19,910 observations.

Table 1.1. Descriptive statistics – Average of the main variables.

| | SMEs | | LARGE FIRMS | |
|---|---|---|---|---|
| | EXPORTERS | NON-EXPORTERS | EXPORTERS | NON-EXPORTERS |
| Total employment | 65.198<br>(53.376) | 29.517<br>(32.506) | 754.224<br>(1335.788) | 479.987<br>(569.471) |
| Permanent employment | 57.602<br>(49.312) | 23.955<br>(28.201) | 668.384<br>(1215.701) | 418.61<br>(535.993) |
| Temporary Employment | 7.596<br>(15.231) | 5.562<br>(11.633) | 85.841<br>(198.778) | 61.377<br>(103.409) |
| $Innov^{Product}$ (dummy) | .219<br>(.414) | .066<br>(.249) | .382<br>(0.486) | .207<br>(.406) |
| $Innov^{Process}$ (dummy) | .32<br>(.466) | .174<br>(.379) | .519<br>(0.500) | .382<br>(.486) |
| Recessive_Demand (dummy) | .316<br>(.465) | .331<br>(.471) | .246<br>(.431) | .2<br>(.4) |
| Recessive_Index | 55.137<br>(31.879) | 58.512<br>(32.323) | 49.223<br>(31.500) | 46.012<br>(32.75) |
| Financial_Restrictions | .054<br>(.821) | .182<br>(.800) | -.315<br>(.836) | -.304<br>(.755) |
| Growth_Domestic_Sales | -.05<br>(.469) | -.049<br>(.335) | -.007<br>(.54) | .042<br>(.373) |
| Capacity utilization (%) | 77.959<br>(17.008) | 77.178<br>(19.073) | 82.279<br>(13.894) | 81.868<br>(14.536) |
| High capac. utiliz. (dummy) | .575<br>(0.494) | .586<br>(.493) | .674<br>(.469) | .695<br>(.461) |
| Average_Wage (euros) | 32,160.61<br>(27,544.284) | 25,097.394<br>(17,902.068) | 40,110.635<br>(13,707.006) | 40,365.316<br>(16,167.42) |
| Intermediates price change (%) | 4.012<br>(8.332) | 4.292<br>(7.701) | 3.318<br>(8.829) | 3.608<br>(7.868) |
| LabProd (euros) | 199,873.19<br>(242,771.03) | 109,161.01<br>(126,194.37) | 306,954.89<br>(379,822.45) | 284,071.52<br>(233,222.05) |
| rat_temporary | .116<br>(0.174) | .167<br>(0.234) | .121<br>(0.145) | .142<br>(0.172) |
| Foreign participation (dummy) | .142<br>(0.349) | .018<br>(.134) | .462<br>(0.499) | .233<br>(.423) |
| Age (years) | 30.552<br>(21.678) | 22.604<br>(17.373) | 41.985<br>(25.442) | 39.987<br>(29.267) |

Note: (i) Standard deviation in parenthesis. (ii) A detailed description of the variables used is provided in Table A1.1. in Appendix 1.

Firstly, there are differences between SMEs and large firms at first sight. On average, regarding employment, SMEs not only employ less workers, but also pay lower wages and are less productive in comparison with large firms. They also have more limitations in the sense that they introduce fewer innovations, have less capacity used and

receive less foreign participation. In addition, they suffer more recessive periods, also having more financial restrictions and suffering more variation in the prices of their intermediate inputs. Finally, they are younger.

Secondly, regarding the differences between exporters and non-exporters, it is noteworthy that, regardless of the firm's size, on average, exporters are larger, innovate more, are more productive, have more foreign participation and are older. On the contrary, non-exporters suffer more financial constraints, present more variation in the prices of their intermediate inputs and employ relatively more temporary workers.

Hence, SMEs and large firms are different, and being an exporter also plays a key role. However, it is interesting as well to see the differences in some key factors for this study during the recession. In other words, it is remarkable to see how exports, employment and financial constraints have evolved before and after the Great Recession. To shed light on this direction, we find in first place that most of large firms in Spain are involved in export activities, while the percentage of SMEs that do so is much lower (see Table 1.2).[10]

Table 1.2. Export Participation of Large firms and SMEs during the pre-slump and slump periods.

| | | **Mean (%)** |
|---|---|---|
| **Large firms** | Pre-slump | 92.35 |
| | Slump | 93.66 |
| **SMEs** | Pre-slump | 51.36 |
| | Slump | 61.97 |

Source: Data from ESEE (Spanish Survey on Business Strategies, SEPI Foundation). Own elaboration. Pre-slump corresponds to the years 2000-2008. Slump corresponds to the years 2009-2014.

[10] SMEs means Small and Medium Enterprises (that is firms with 10-200 employees).

The number of Spanish manufacturing large firms that export was more than 90% and, in the recession, this share was still so high, although it experienced a slight increase. Conversely, the situation for SMEs was different, since the percentage of firms in this group that export increased from 51.4% in the precrisis period to nearly a 62% in the slump period. Thus, the evolution of SMEs in terms of export participation is, at least, considerable and remarkable and reveals a relevant incorporation pattern to this internationalisation activity.

As a matter of fact, this increase in export participation for SMEs was not common in all European countries. After the crisis, the general trend in Europe was a decline in the export intensity of SMEs. Germany or France saw how their exports from SMEs declined after the crisis, accounting in 2014 for 20% of total exports, while Spain was able to not only increase the number of exporter SMEs as shown in Table 1.2, but also to rise their value up to a 50% of total exports in 2014.[11]

In addition, after the fall in internal demand previously shown in Figure 1.5, among SMEs the exporter firms were the ones presenting better results in terms of employment, as it is shown in Table 1.3. Thus, exporting SMEs seem to show greater resilience in terms of employment in a period of recession than non-exporting SMEs.

Table 1.3. Employment for exporter and non-exporter SMEs during the pre-slump and slump periods.

| | | **Mean** | **Std. Dev.** |
|---|---|---|---|
| **Exporter SMEs** | Pre-slump | 63.16 | 53.17 |
| | Slump | 67.54 | 53.52 |
| **Non-exporter SMEs** | Pre-slump | 30.74 | 32.78 |
| | Slump | 27.23 | 31.87 |

Source: Data from ESEE (Spanish Survey on Business Strategies, SEPI Foundation). Own elaboration. Pre-slump corresponds to the years 2000-2008. Slump corresponds to the years 2009-2014.

[11] This data was retrieved from OECD data (https://data.oecd.org/trade/exports-by-business-size.htm).

Finally, as discussed in section 1.2 and as shown in the descriptive statistics table (Table 1.1), being an SME has also implications when it comes to financial constraints, since their export or employment growth strategies, among others, may depend on access to financial resources. In Table 1.4, for the period analysed by us in this chapter, we show that large firms obtain cheaper bank financing than SMEs and that SMEs obtain, compared to large firms, more expensive bank financing during the recession period. This table offers the annual deviation of the financial cost of the long term debt of firms with financial institutions with respect to the average cost paid by other firms in the same year.

Table 1.4. Financial costs (deviations with respect to the mean) for SMEs versus large firms during the pre-slump and slump periods.

| | | **Mean** | **Std. Dev.** |
|---|---|---|---|
| **Large firms** | All periods | -0.30 | 0.84 |
| | Pre-slump | -0.21 | 0.76 |
| | Slump | -0.50 | 0.95 |
| **SMEs** | All periods | 0.11 | 0.81 |
| | Pre-slump | 0.09 | 0.78 |
| | Slump | 0.13 | 0.84 |

*Source*: Data from ESEE (Spanish Survey on Business Strategies, SEPI Foundation). Own elaboration. Pre-slump corresponds to the years 2000-2008. Slump corresponds to the years 2009-2014.

Therefore, we can have a first intuition after reviewing the literature and data. SMEs may suffer more during the crisis in terms of financial constraints, but their export participation may help them become more resilient in terms of employment. In the following section, we will continue with our theoretical framework, our empirical approach and the estimation results in order to answer our main research questions in the chapter.

## 1.4. Theoretical framework and estimation results

As already mentioned from the beginning, we aim to disentangle the role of export participation on SMEs employment resilience during recessionary periods particularly affecting domestic demand. This type of recessionary periods may affect negatively firms' employment directly due to the lack of demand, the decrease in production and, hence,

the firing of workers. However, for some firms this can be just a short-term effect in employment that can be partly offset by entering export markets. The moderating effect of the export strategy on job destruction in a situation of lack of domestic demand can be theoretically understood if, starting from a traditional model à la Melitz (2003), with constant marginal production costs, we introduce increasing marginal production costs. This type of model is fully developed in Almunia et al. (2021) and allows establishing a theoretical causal link between drops in domestic demand and greater firms' incentives to export (a substitutability of domestic demand by exports termed "venting out"). The way in which they introduce in their theoretical model increasing marginal production costs is with a close to reality cost structure where a firm combines a fixed factor such as capital with a more flexible factor such as labour. This type of cost structure results in a convex curvature of the firm's marginal cost function, which implies that in the short term, that is, when the installed productive capacity cannot be varied, the closer a firm is to its capacity constraint, the more pronounced the slope of its marginal cost curve. A result that derives directly from this curvature is that it is those firms closest to their production capacity limit that will benefit the most in the short term from a drop in marginal costs when their domestic demand falls. If this prediction of the model is true, it will imply that there is a negative causal link between domestic demand and exports that is mainly driven by firms with high utilization of their production capacity. When these firms in the short term adapt to the situation of domestic demand by laying off workers, they move down their marginal cost curve, release productive capacity, can lower prices and be more competitive. All this together makes their export profits increase and, therefore, their incentives to export grow.

In short, once firms export, regardless of whether exports are encouraged by the aforementioned mechanism or by a different one, they begin to use their productive

capacity released in the short term and hire workers to respond to the increase in external demand. Therefore, in our employment equations we expect both a negative direct effect of the deterioration of domestic demand conditions and an attenuation of this effect for firms that export. Delving into these equations, we can interpret the two effects as follows based on the arguments in Almunia et al. (2021) theoretical model: 1) in the short term, when facing a fall in domestic demand, firms reduce production by diminishing their use of flexible inputs (e.g., workers) relative to their use of fixed inputs (e.g., capital). In our estimated employment equations, this effect is expected to be captured by the variable that controls for recessive demand. Moreover, not only that, it is also expected that this adjustment in employment will be greater for temporary workers, the most flexible part of the firm's workforce with the lowest firing costs. 2) The fall in short-term marginal costs due to the behaviour of domestic demand frees up production capacity that can be used to satisfy external demand when firms export. This substitution effect for exporters of domestic demand by foreign demand is what explains the moderating effect of exporting on job destruction generated by a domestic demand crisis. In our estimated employment equations, the moderating effect that modifies the initial job destruction is expected to be captured by a positive coefficient on the crossed product variable between demand conditions and the firm's export strategy.

Nevertheless, is it indeed true in our data that the "venting out" hypothesis holds, and thereby helps us to explain the aforementioned moderating effect? Answering this question is the reason why, before presenting our estimation results for the employment equations, we are interested in explaining the firm's decision to export. In addition, we will also use the export decision equation to check whether the prediction in Almunia et al. (2021), whereby the firms with the highest production capacity used are the ones that react most strongly to a drop in internal demand, becoming exporters, holds.

For these purposes, we present in Table 1.5 the results of a *probit* model that estimates this strategic firms' decision. We include pre-sample means of the dependent variable in the estimation equation to deal with correlated unobserved individual heterogeneity. In particular, we control for correlated unobserved individual heterogeneity through the method in Blundell et al. (1999, 2002), which is applicable in both linear and non-linear models. In fact, it is very convenient for the case of nonlinear models due to the so-called incidental parameter problem in fixed effect estimators for this type of models. Blundell et al. (1999, 2002) approach implies modelling firms' unobserved heterogeneity as a linear function of pre-sample means of the dependent variable plus a firm-specific random term that follows a conditional normal distribution. Therefore, this methodology to allow firms' unobserved individual effects to be correlated with regressors, requires including the pre-sample means $Exp_{i,Mean,0}$ among regressors in the export equation. As we start estimation in year 2000 and regressors are lagged one period, we use as pre-sample period 1997 and 1998.[12]

We also correct in the export equation for non-random attrition due to observability of SMEs export decisions only for firms continuing in operation. To consider this problem we implement a Heckman's (1979) two-stage selection correction. In a first stage, we estimate with a *Probit* model the probability of firms' survival until period *t* (from our sample period), conditional on their survival until period *t-1*. From the estimates of this survival equation (estimated with 19,866 observations corresponding to 2,824 firms), we construct the Heckman's lambda continuation in operation term (also known as the inverse Mills ratio). Next, in a second stage, we include this term among regressors in the

[12] Blundell et al. (1999) suggest that permanent individual effects might be captured by the entry pre-sample mean of the dependent variable, which acts as a sufficient statistic for unobserved firm heterogeneity.

export decision equation.[13] At the bottom part of Table 1.5, we show for the export equation the estimated coefficient associated to the lambda selection correction term. Its statistical significance is indicative of the need to include it in the export equation to avoid bias caused by non-random attrition in our estimation sample.

In the *Probit* model for firms' survival we explain firms' continuation in operation until period *t* with the one period lagged regressors that follow: the firms' export status, the degree of firms' innovativeness as captured by the introduction of product or process innovation, a variable for the degree of financial restrictions that firms face, demand conditions as proxy by an index of market recession (which has been constructed as the opposite of the market dynamism index provided in the survey and, hence, now the closer to 100 the worse the market situation),[14] some variables to proxy for changes in competitiveness due to supply-side factors (cost shifters) such as log of labour productivity, log wage per worker, the (initial) firm-level share of temporary workers or the percentage change in prices of intermediates, control variables at the firm level (such as a firm size dummy distinguishing between small and medium size firms and the log of age), time dummies and sector dummies.[15] In addition, we add a variable (lagged one period) on the utilization of the firm's productive capacity (percentage of the production

[13] This term is generically calculated as the ratio of the density over the distribution function of a normal distribution ($\phi(Z\theta)/\Phi(Z\theta)$), in which the argument ($Z\theta$) is the index function from a *Probit* model with a generic vector of regressors *Z*.

[14] The index of market dynamism (that ranges from 0 to 100) is a weighted average of the recession, stability, or expansion situation of the 5 most relevant different markets where firms operate.

[15] The (initial) sample period firm-level share of temporary workers is introduced in the firms' continuation in operation equation in case labour costs have not been fully accounted for by our firm-level measures of productivity and average wages. Note that there may be a difference in skills between the two types of workers biased towards permanent workers and, therefore, also a productivity differential in favour of the latter. In estimating the *Probit* model for the firms' continuation in operation equation, we obtain similar results when instead controlling for the one period lagged firm-level share of temporary workers. Although nothing changes, we prefer to be more conservative and not include in this equation as a regressor a more contemporary firm-level share of temporary workers, in case this may interfere with our subsequently estimated employment equations.

capacity that is being used). As we have already mentioned, this variable is expected to be crucial in a capacity-constrained model (Almunia et al. 2021). However, unlike in the subsequent export equation, in the firms' continuation in operation equation, a lower utilization of the firms' productive capacity may be indicative of an economic slump and, therefore, reinforce the role of the index of market recession in this equation.

As for the variable of financial restrictions that firms may face, following Beneito et al. (2015) and Máñez et al. (2014), we construct, with information on the financial statements in the ESEE survey, a measure of the financial cost of firms' debt with financial institutions. Although the financial crisis has gone hand in hand with a significant decrease in the average cost of debt, it was also characterised by a severe difficulty of access to credit (see Figure 1.6 for the decrease in the yearly growth rate of loans to non-financial institutions in Spain). Unfortunately, we do not have information in the survey to capture this firm's dimension of financial restrictions. Hence, even if we acknowledge, as in Almunia et al. (2021), that firms' financial restrictions could have been better captured by a firms' measure of credit rationing, similar to them, our assumption here is that firms facing higher costs of debt should be the ones who suffer most from credit restrictions. Given this assumption, we introduce in estimation a transformation of the firm's financial cost variable that consists of its *per* year deviation with respect to the average cost paid by other firms in the same year.[16]

Due to the nature of the dependent variable in the survival equation, with a value of 1 if the firm survives in period *t* and 0 otherwise, we cannot treat unobserved correlated individual heterogeneity with the inclusion of pre-sample means of the dependent

[16] We have also tried with the alternative measure of calculating the cost of debt deviation with respect to the average of the sector to which the firm belongs. In spite of results being qualitatively similar, we believe that our choice is more reliable since there may be sectors particularly affected by adverse borrowing conditions and this would not be reflected in a measure that uses sector averages for comparison.

variable in the equation to estimate. These means for pre-sample years would be, by definition, 1 for all firms. Note that if firms are still alive in future periods, they were necessarily previously alive. For this reason, and also due to the so-called incidental parameter problem in fixed effect estimators for nonlinear models, this particular equation is first estimated with a random effects *Probit*. However, since the estimated proportion of the total variance contributed by the variance component at the panel level is not statistically significantly different from zero (see end of Table A1.2 in Appendix 1), the panel *Probit* estimator is not different from the pooled *Probit* estimator. Due both to this and to the fact that this equation is merely an auxiliary equation in our work, the final estimates that we present for this equation correspond to those of the more efficient pooled *Probit*.

According to the results in Table A1.2 in Appendix 1 (column 1: original annual data) from estimation of this auxiliary equation, the *Probit* model of firms' survival *versus* death, we see that for SMEs, exporting, being more productive or introducing innovations (mainly process innovations but also product) increase their likelihood of survival. On the other hand, SMEs that suffer more financial restrictions, face a more recessive market situation, pay higher wages per worker, have a higher share of temporary workers, or suffer a greater increase in the prices of their intermediate inputs, reduce their chances of survival. As expected, a lower utilization of the firms' productive capacity reinforces the negative role of the recessive index in firms' survival. Finally, foreign participation *per se* does not guarantee survival and we find evidence of positive duration dependence since the older a firm is the greater its prospects for survival.[17]

[17] We find that foreign capital participation has a negative effect on firms' survival. This result has been already found in previous studies with the ESEE data (see, for instance, Beneito et al., 2015).

Although ESEE providers declare that new firms are incorporated in the panel in order to avoid reductions in population coverage across industries and size-segments, on the survey website there are some years in which there is no entry in the sample.[18] To check whether our results in column 1 of Table A1.2 in Appendix 1 are robust to this potential noise in the estimation of the survival equation, we add column 2 estimates. Unlike column 1, in which each observation in the time dimension corresponds to one year, column 2 presents estimates where each observation in the time dimension corresponds to a three-year rolling average of each variable for each firm.[19] Since with this approach the results are remarkably similar, we trust our results in column 1 as plausible and stick to them in order to take advantage of the full-time variation in our annual data.

After having tackled both the econometric issue of correlated unobserved individual heterogeneity and that of non-random attrition into the sample, we estimate the export equation by pseudo-simulated maximum likelihood applied to the likelihood function of the following panel *Probit* model (Roodman, 2011):[20]

$$Exp_{it} = \begin{cases} 1 & if \quad \alpha + \theta_0 Exp_{it-1} + \theta_1 Innov_{it-1}^{Prod/Proc} + \theta_2 Financial\_Restrictions_{it-1} + \theta_3 Growth\_Dom\_Sales_{it-1,t} + \varphi C_{it-1} + \gamma Z_{it-1} + s_j + \delta_t + \varepsilon_{it} \geq 0 \\ 0 & otherwise \end{cases} \tag{1.1}$$

where $\theta_0$ controls for persistence in the export strategy generated by sunk costs associated to this activity; $\theta_1$ is a vector that accounts for firms' expected returns from exporting to be affected by firms' product and process innovation activities; $\theta_2$ takes into

[18] https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp.

[19] Since the dependent variable is a binary variable 0/1 and we are estimating a *Probit* model, the rolling average of the dependent variable is set to 0 when in a particular interval the firm dies.

[20] This equation, once controlling for correlated unobserved individual effects by pre-sample means of the dependent variable, is estimated with a random effects panel *Probit*, since still the estimated proportion of the total variance contributed by the variance component at the panel level is statistically significantly different from zero (see end of Table 1.5).

account whether firms that are more financially constrained face problems that decrease their likelihood of exporting;[21] $\theta_3$ captures the effect of demand conditions on firms' decisions to invest in export activities; the vector $C_{it-1}$ includes (following Almunia et al., 2021) variables affecting firms' competitiveness from the supply side such as log labour productivity, log average wages, the (initial) firm-level share of temporary workers and price variation of intermediate inputs.[22] All these factors may encourage exports by affecting production costs (costs shifters). Furthermore, average wages may have undergone a downward adjustment in response to the effects of a recession in the labour market (the so-called "internal devaluation"). These factors are relevant to our export equation since they allow us to distinguish between the export incentives generated by "internal devaluation", production costs and supply side effects from those generated by a firm's strategic reaction to the fall in internal demand. Additionally, the vector $Z_{it-1}$ includes control variables at the firm level (the foreign capital participation dummy, log age and the dummy variable for medium *versus* small firms). Sector ($s_j$) and year ($\delta_t$) dummies are also included. Finally, $\varepsilon_{it}$ is a composite error term that includes permanent individual unobserved heterogeneity and an idiosyncratic error term.

In the export equation, the variable for demand conditions is simply the growth (in percent) of domestic sales (from period *t-1* to *t*). The reason for this is to verify with our data the hypothesis of "venting-out" in Almunia et al. (2021), which show that once

[21] The financial restrictions variable is the same one already included in the continuation in operation *probit* model previously described.

[22] In estimating the *Probit* model for the firms' decision to export, like in the continuation in operation equation, we obtain similar results when instead controlling for the one period lagged firm-level share of temporary workers. Although nothing changes, we prefer to be more conservative and not include in this equation as a regressor a more contemporary firm-level share of temporary workers.

supply factors are controlled, there is a negative relationship between domestic sales growth and export decisions due to a firms' strategic reaction.

Next, we comment on the estimates for expression (1.1) shown in Table 1.5 (columns 1 and 2). First, as for the continuation in operation correction term included, it is statistically significant. Its negative sign suggests that unobservables that increase firms' survival decrease the likelihood of exporting. This interesting result reinforces the idea that SMEs use the export strategy as a means to avoid death. Consequently, when death is less likely to occur some SMEs may be discouraged from entering foreign markets. Furthermore, we find high persistence (state dependence) in the firm's export status, which is in favour of the existence of sunk costs in that activity. A different type of persistence generated by the presence of unobserved individual heterogeneity (captured by export pre-sample means) also exists. We also find that innovation activities affect positively the payoffs from exporting. Moreover, we confirm that the previously more productive firms are the ones that self-select into exports.

Table 1.5. Panel Probit estimates for SMEs export strategy.

| Variables | (1) $Export_t$ | (2) $Export_t$ |
|---|---|---|
| $Export_{t-1}$ | 1.912*** | 1.920*** |
| | (0.072) | (0.072) |
| $Innov_{t-1}^{Product}$ | 0.158*** | 0.157** |
| | (0.061) | (0.062) |
| $Innov_{t-1}^{Process}$ | 0.115** | 0.121** |
| | (0.054) | (0.053) |
| $Financial\_Restrictions_{t-1}$ | -0.041* | -0.041* |
| | (0.025) | (0.025) |
| $Growth\_Domestic\_Sales_{t-1,t}$ | -0.127** | 0.003 |
| | (0.057) | (0.100) |
| $Growth\_Domestic\_Sales_{t-1,t} * High\ capac.utiliz._{t-1}$ | | -0.239** |
| | | (0.115) |
| $High\ capac.utiliz._{t-1}$ | | 0.014 |
| | | (0.055) |
| $log\ (Average\_wage_{t-1})$ | 0.093 | 0.087 |
| | (0.098) | (0.100) |
| $Intermediates\ price\ change(\%)_{t-1,t}$ | -0.002 | -0.003 |
| | (0.003) | (0.003) |
| log $(LabProd)_{t-1}$ | 0.284*** | 0.286*** |
| | (0.047) | (0.047) |

| | | |
|---|---|---|
| $Ratio\ temporary\ employment_0$ | -0.014 | -0.018 |
| | (0.131) | (0.131) |
| $Foreign\ participation_{t-1}$ | 0.198† | 0.195† |
| | (0.124) | (0.125) |
| $Medium_{t-1}$ | 0.409*** | 0.408*** |
| | (0.058) | (0.058) |
| log $(Age_{t-1})$ | 0.041 | 0.043 |
| | (0.039) | (0.039) |
| $Export\ Presample\ Mean$ | 2.172*** | 2.163*** |
| | (0.170) | (0.169) |
| $Lambda\ cont.\ operation$ | -0.935* | -0.820† |
| | (0.497) | (0.531) |
| $Constant$ | -5.600*** | -5.571*** |
| | (0.810) | (0.825) |
| Proportion of total variance contributed by the panel level variance | 0.415*** | 0.413*** |
| | (0.036) | (0.036) |
| *Log pseudo-likelihood* | -3271.7460 | -3268.4431 |
| $N\ observations$ | 18,167 | 18,165 |
| $N\ firms$ | 2,714 | 2,714 |

*Note*. All estimations include industry and time dummies. Clustered robust standard errors are in parentheses. When a previously estimated variable is included among regressors, we provide block-bootstrapped standard errors in parentheses. ***, **, and * mean significant at the 1 percent, 5 percent, and 10 percent level, respectively. † means slightly above 10 percent level (11% and 11.7% for the Foreign participation variable in columns 1 and 2, respectively, and 12.2% for the Lambda continuation in operation variable in column 2).

Regarding the results for the variables capturing firms' financial restrictions and demand conditions, we obtain the following: first, that financial restrictions are binding and, second, we confirm the "venting out" hypothesis in Almunia et al. (2021). This means that a slump in domestic sales encourages SMEs' export decisions (see in Table 1.5 that the coefficient on the variable *Growth_domestic_sales* in column 1 is negative and significant). However, the "internal devaluation" argument that operates through the average wage variable is not supported by our data, since this variable is not statistically significant. Neither is the ratio of temporary workers nor the price variation in intermediates. Therefore, from the group of supply side variables (or costs shifters), the one that is relevant is labour productivity.

As for the firm-level control variables, the ones statistically significant are foreign capital participation and the medium-size dummy variable, but not the age variable. The positive signs of the coefficients associated to these variables indicate, first, that being

foreign participated may facilitate access to foreign markets and, hence, facilitate exports and, second, that in the group of SMEs, small firms are less likely to export.

Before leaving the results on the firms' export decision and going on to comment on the employment equations, we must remark on an important result in our specification in column 2 of Table 1.5. This column presents an extension of our baseline specification of the export equation in column 1. This extension incorporates two new regressors to the previous specification: a dummy variable with value 1 when the utilization of the firm's productive capacity is above the median (mean) in the sample (80%), 0 otherwise, and the crossed product of the variable growth in domestic sales and the previous dummy. The purpose of this extension of the model is to directly test the theoretical prediction in Almunia et al. (2021) according to which, with increasing marginal costs in production, it is the firms with the greatest use of their productive capacity that benefit the most from their short-term downward movement in their marginal cost curve (caused by their adjustment in flexible factors to the decrease in domestic demand). These firms should be the ones that can lower prices the most by reducing marginal costs and, therefore, those that can increase competitiveness the most and have more export incentives and opportunities. In fact, that is what our results from column 2 show. The growth variable of domestic demand is no longer significant but, on the contrary, it is significant for exporting firms for which it also maintains its negative sign. The coefficient for the variable growth in domestic sales for exporters in column 2 of Table 1.5 has a value of -0.236 (with a *p*-value of 0.000), and it comes from adding the coefficient of the growth variable of domestic sales to the coefficient of the cross product of this variable with the dummy variable of firms with high utilization of their production capacity.

Now that the theoretical issues relevant to our work have been discussed and some of them tested, we can move on to presenting our employment equations. We do not have

to forget that the final goal of our work is to say something about the role of export participation on SMEs employment resilience during recessionary periods particularly affecting domestic demand. Thus, in order to achieve it, we estimate a baseline specification for the employment equation of a firm that does not yet distinguish workers by type of contract (temporary or permanent) nor does it allow export participation to play a specific role in situations of adverse demand. Hence, in this first specification, we use the log of firms' employment as the dependent variable in an equation where the main explanatory variables are a firm's export participation dummy, a variable capturing firms' demand conditions, and some controls. In particular, we estimate the following dynamic equation that relates the firms' number of workers with the firms' export participation strategy:

$$\log(Emp_{it}) = \beta_0 + \beta_1 \log(Emp_{it-1}) + \beta_2 Exp_{it-1} + \beta_3 RecessDemand_{it\text{-}1} + \gamma Z_{it-1} + s_j + \delta_t + u_{it} \qquad (1.2)$$

where $\log(Emp_{it})$ is the log of the number of workers of firm *i* in period *t* and $\log(Emp_{it-1})$ is its one period lagged value; $Exp_{it-1}$ is a dummy variable that captures if the firm exported in period *t*-1. Therefore, $\beta_2$ measures the firm's employment premium from exporting. Firms' demand conditions are captured by a dummy variable ( $RecessDemand_{it\text{-}1}$) that is constructed from the index of market dynamism provided by the ESEE. The index of market dynamism (that ranges from 0 to 100) is a weighted average of the recession, stability or expansion situation of the 5 most relevant different markets where firms operate. From this index, the dummy variable $RecessDemand_{it\text{-}1}$ is constructed as being equal to one when the index value is between 0 and 35. Doraszelski and Jaumandreu (2013) also use this information from the ESEE to proxy for the macroeconomic business cycle in Spain. They show that in the 1990s, this variable mirrors the macroeconomic cycle since, for instance, in growth periods firms tend to

report that their markets are in expansion. Furthermore, we also corroborate this in our sample period in this chapter since from 2000 to 2008 the percentage of firms declaring a recessive demand is 17.88%, while in the period 2008 to 2014 the percentage grows to 46.84%.[23] Furthermore, the recessive demand dummy is clearly dominated by the behavior of the internal demand, since even for exporters the percentage of domestic sales is 72%. Equation (1.2) also includes a vector $Z_{it-1}$ of control variables at the firm level that comprises our measure of firms' financial restrictions and the log of firms' age. In addition, we also include in (1.2) a vector of time ($\delta_t$) and sector dummies ($s_j$). Finally, $u_{it}$ is a composite error term equal to $\alpha_i + e_{it}$, where $\alpha_i$ represents individual unobserved heterogeneity and $e_{it}$ is an idiosyncratic error term. The reason why our specification in (1.2) is dynamic is being able to consider persistence in firms' employment.

Since in this chapter we are not only interested in firms' total employment but also in its composition as regards types of contracts (permanent or temporary), one of the departures from our baseline specification in (1.2) will consist of substituting total employment for the number of permanent or temporary workers in the firm.

Estimation results for equation (1.2) are presented in Table 1.6. Columns 1, 2 and 3 correspond to the firms' total number of workers, number of workers under permanent contracts and number of workers under temporary contracts, respectively. In addition, in columns 4, 5 and 6 our baseline specification in (1.2) is widened to include further among regressors the interaction term between the export dummy and the dummy variable for adverse demand conditions. The purpose of this extension is precisely to answer our main

[23] The reason why in the employment regressions we use the dichotomous indicator of recessive demand instead of the continuous (from 0 to 100) recessive index is to easy interpretation of the cross product variables between the recessive demand (0/1) indicator and the firms' business strategy of exporting (also a dichotomous variable), which will appear in many of our specifications of the employment equation derived from the baseline in (1.2).

research question in this work, which is whether participating in the export market acts as a buffer against the adverse effects of the economic cycle on firms' employment. We wonder if exporting helps mitigate job losses in recessionary periods.

From a methodological point of view, we initially tackle two econometric issues. The first is related to firms' unobserved heterogeneity (unobserved individual effects $\alpha_i$), which may be correlated with regressors in (1.2) as simply by model construction they are correlated with the included lagged dependent variable among regressors. Although our regressions for total employment and permanent employment are linear, this is not the case for the temporary employment regression. In this case, we find in our data that 42% of SMEs declare to have zero temporary workers. Given the considerable amount of zeros, we will use a *Tobit* model for estimation of the temporary workers equation. Given that in this case the model would not be linear, and also to give a homogeneous econometric treatment to individual firms' effects in all employment equations (which will facilitate the interpretation of comparative results between permanent or temporary employment), we chose to control them again using the correlated individual effects methodology developed by Blundell et al. (1999, 2002), which is applicable to both linear and non-linear models. Hence, we model the distribution of $\alpha_i$ conditional on the pre-sample mean of the dependent variable $\log\left(Employment_{i,Mean,0}\right)$ in the following way:

$$\alpha_i = \alpha_0 + \alpha_1 \log\left(Employment_{i,Mean,0}\right) + \pi_i \tag{1.3}$$

Where $\pi_i|\left(log\left(Employment_{i,Mean,0}\right)\right) \sim Normal(0, \sigma_\pi^2)$. Next, we add the variable $\log\left(Employment_{i,Mean,0}\right)$ among regressors in (1.2). This new regressor is calculated as the within firm mean of $\log\left(Employment_{i,Mean,0}\right)$ for the considered pre-sample years. Since our sample period for estimation starts at year 2000 and most of

regressors are lagged one period to avoid potential simultaneity bias, we consider as pre-sample years 1997 and 1998. This method allows for correlation of firms' individual effects with regressors in (1.2). We observe at the bottom of Table 1.6 that persistent firms' effects are relevant to explain firms' number of workers. Persistent firms' effects affecting positively employment might be indicative of higher quality or managerial ability. Notice that modelling in this way unobserved individual heterogeneity requires in (1.2) that the variable $\log(Employment_{i,Mean,0})$ be replaced by $\log(Permanent\ Employment_{i,Mean,0})$ or $\log(Temporary\ Employment_{i,Mean,0})$ in the regressions where the dependent variables are the number of permanent or temporary workers, respectively.

The second econometric issue is related to the fact that we only observe employment conditional on firms surviving until period *t* and, hence, estimated coefficients in the employment equations may suffer from non-random attrition bias when, for instance, firms that survive are simultaneously more likely to export and have larger workforces. If this was the case, we would be facing an endogenous exit of firms from the market. To solve it, we follow the same strategy as in the export equation, implementing therefore the Heckman's (1979) two-stage selection correction.

After having tackled these econometric issues, we will now comment on the results obtained for the main regressors in the employment equations (Table 1.6). In our specifications in columns 1, 2 and 3 we obtain that there is a high persistence (state-dependence) in the evolution of SMEs employment (the coefficient on the variable $\log(Employment_{it-1})$ is positive and significant for total, permanent or temporary workers). The positive and significant estimates for $\beta_2$ (associated to the export decision in period *t-1* in expression (1.2)) for total and permanent employment suggest that exporting allows SMEs to maintain a higher level of employment. These rewards in

employment are 2.7% for total employment and 4.4% for permanent employment. However, there is a non-significant effect of SMEs export participation on temporary employment. Hence, exporting contributes to increasing the number of firm's workers, and since it seems to be more oriented to the hiring/consolidation of permanent workers, it contributes to the change in the composition of SMEs workforce by increasing the ratio of permanent to temporary workers. This can be interpreted as that exporting contributes to increasing the quality of contracts within the firm. Consequently, an exporting firm will tend to have a higher level of employment with a higher number of permanent contracts and a lower proportion of temporary workers compared to a non-exporting firm. In addition, for SMEs, facing a recessive demand has a negative impact on their level of employment in all cases (total, permanent or temporary employment). However, as expected, employment destruction related to recessive demand conditions is much larger for temporary employment. In particular, firms have a decrease almost four times greater in temporary contracts than permanent contracts, since being in a recessive period reduces the number of temporary workers by 16.9% and that of permanent workers by 4.5%. Total employment and, specially, temporary employment are much more sensitive to firms' recessive periods than to firms' exporting decisions. For the case of permanent employment, both effects are of a similar magnitude but with an opposite sing.

As already highlighted above, in this chapter we are especially interested not only in the direct role of exports in employment but also in its particular effect during recessions. This leads us to add to our previous specifications the cross variable $Exp_{it-1} \times RecessDemand_{it-1}$. The estimation results of these widened regressions are provided in columns 4, 5 and 6 of Table 1.6. Interestingly enough, an exporting firm can offset around a half of the effect of a recessive period on employment destruction. This comes from the effect that exporting has on permanent employment in recessions, since

no significant effect is found for temporary employment. In addition, for exporters in recessive periods there is an extra increase in the ratio of permanent to temporary workers. In particular, according to our results, SMEs exporters (in comparison to non-exporters) not only get higher total/permanent employment in good times (1.7% / 3.4% reward, respectively) but specially this advantage is reinforced when facing recessive demand conditions (1.7%+3.5%=5.2% / 3.4%+3.3%=6.7% reward, respectively). Hence, for SMEs, exporting during recessive periods helps offset the negative effect that a downturn in the cycle has *per se* in SMEs employment. This compensation acts for permanent employment and, therefore, favours the ratio of permanent to temporary workers.

As regards control variables in estimation, for financial restrictions no effect on employment has been found, either for permanent or temporary workers. This may be coherent with the fact of this variable only affecting employment through its indirect effect on firms' survival chances and export decisions. The effect of firm age is negative and significant and may also suggest that once controlling for non-random selection determining continuation in operation, where age is a clear factor of firms' survival, the age variable in the employment equations might be capturing instead the effects of the product life cycle and its maturity.

Finally, in columns 7 to 12, we extend the specifications in columns 4 to 6 to control for some confounding factors that may both affect firms' export decisions and firms' employment. The confounding factors considered are variables that were not originally included in our employment equations but that are significant to explain the firms' export decision. A clear candidate for this robustness check of our benchmark results in columns 4 to 6 is undoubtedly productivity. Notice that in a Melitz (2003) type of model, export is a function of productivity and when productivity improves, both the probability of exporting and the size of the firm grow. The results of this extension are in columns 7 to

9 in Table 1.6. Labour productivity is statistically significant and with a positive sign in the employment equations (although with a more significant and higher coefficient for permanent employment than for temporary employment). Nevertheless, the inclusion of productivity in the employment equations does not alter the previous results or the previous conclusions that we derived from columns 4 to 6.

In a second robustness check, the results of which we present in columns 10 to 12 in Table 1.6, we control for potential additional confounders that affect the decision to export. These are related to firms' innovation activities, such as the introduction of new products and processes, and the presence of foreign capital. Productivity continues to be statistically significant and with a positive sign, process innovation is positively related to both types of employment, permanent and temporary, and product innovation and the participation of foreign capital only present effects on permanent employment. Most importantly, our previous benchmark results and the conclusions in columns 4-6 still hold.

Overall, which are the summary results from Table 1.6? First, there is persistence in employment both coming from state dependence and individual unobserved heterogeneity. Second, for SMEs, export activities have a positive effect on total employment that is especially relevant in bad times and that only occurs through permanent employment. Hence, there are compositional effects on employment from the export activity that work in the direction of increasing the ratio of permanent to temporary workers. Thus, for SMEs, we have obtained rewards in employment from exporting. Furthermore, these rewards from the export activity (versus non-exporters) have been reinforced during the most difficult part of the business cycle, helping exporters compensate for declining employment associated with poor demand conditions. In fact, all these effects come from the behaviour of permanent employment, which is also reflected in the total employment of firms.

Moreover, and even more relevant to us, we conclude that with our empirical exercise we provide some evidence on the following two hypotheses already in our theoretical framework at the beginning of section 1.4. First, it seems that in the short term, when facing a fall in domestic demand, SMEs reduce the use of flexible inputs such as labour, and especially temporary workers. Second, exporting SMEs can halve this job destruction in their total employment and this is due to the evolution of permanent workers.

Table 1.6. Export participation and SMEs employment resilience.

| Variables | (1) Total employment | (2) Permanent employment | (3) Temporary employment | (4) Total employment | (5) Permanent employment | (6) Temporary employment | (7) Total employment | (8) Permanent employment | (9) Temporary employment | (10) Total employment | (11) Permanent employment | (12) Temporary employment |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| log (Total Employment)$_{t-1}$ | 0.815*** | | | 0.814*** | | | 0.776*** | | | 0.775*** | | |
| | (0.033) | | | (0.033) | | | (0.025) | | | (0.025) | | |
| log(Permanent Employment)$_{t-1}$ | | 0.768*** | | | 0.768*** | | | 0.720*** | | | 0.718*** | |
| | | (0.034) | | | (0.034) | | | (0.023) | | | (0.023) | 0.728*** |
| log(Temporary Employment)$_{t-1}$ | | | 0.718*** | | | 0.719*** | | | 0.729*** | | | (0.021) |
| | | | (0.019) | | | (0.019) | | | (0.021) | | | |
| Export$_{t-1}$ | 0.027*** | 0.044*** | 0.030 | 0.017*** | 0.034*** | 0.016 | 0.027*** | 0.023*** | 0.004 | 0.027*** | 0.022*** | -0.002 |
| | (0.006) | (0.007) | (0.025) | (0.006) | (0.007) | (0.022) | (0.007) | (0.007) | (0.029) | (0.007) | (0.007) | (0.030) |
| Recessive_Demand$_{t-1}$ | -0.046*** | -0.045*** | -0.169*** | -0.067*** | -0.065*** | -0.200*** | -0.070*** | -0.065*** | -0.214*** | -0.072*** | -0.068*** | -0.221*** |
| | (0.005) | (0.006) | (0.023) | (0.008) | (0.010) | (0.031) | (0.008) | (0.009) | (0.040) | (0.008) | (0.010) | (0.041) |
| Export$_{t-1}$ * Recessive_Demand$_{t-1}$ | | | | 0.035*** | 0.033*** | 0.051 | 0.036*** | 0.036*** | 0.058 | 0.037*** | 0.036*** | 0.057 |
| | | | | (0.010) | (0.011) | (0.042) | (0.009) | (0.010) | (0.052) | (0.009) | (0.010) | (0.052) |
| Financial_Restrictions$_{t-1}$ | 0.000 | 0.003 | -0.009 | 0.000 | 0.003 | -0.009 | 0.001 | 0.003 | -0.009 | 0.001 | 0.003 | -0.009 |
| | (0.002) | (0.003) | (0.011) | (0.002) | (0.003) | (0.011) | (0.002) | (0.002) | (0.010) | (0.002) | (0.002) | (0.010) |
| log(Age$_{t-1}$) | -0.019*** | -0.029*** | -0.108*** | -0.019*** | -0.029*** | -0.108*** | -0.024*** | -0.029*** | -0.112*** | -0.022*** | -0.027*** | -0.111*** |
| | (0.005) | (0.005) | (0.024) | (0.005) | (0.006) | (0.024) | (0.005) | (0.007) | (0.020) | (0.005) | (0.007) | (0.021) |
| log $(LabProd)_{t-1}$ | | | | | | | 0.050*** | 0.051*** | 0.038* | 0.050*** | 0.051*** | 0.033* |
| | | | | | | | (0.006) | (0.007) | (0.020) | (0.006) | (0.007) | (0.020) |
| $Innov_{t-1}^{Product}$ | | | | | | | | | | 0.006 | 0.014** | 0.027 |
| | | | | | | | | | | (0.006) | (0.007) | (0.028) |
| $Innov_{t-1}^{Process}$ | | | | | | | | | | 0.017*** | 0.017*** | 0.063** |
| | | | | | | | | | | (0.005) | (0.007) | (0.024) |
| $Foreign\ participation_{t-1}$ | | | | | | | | | | 0.002 | 0.026** | 0.057 |
| | | | | | | | | | | (0.010) | (0.012) | (0.049) |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| log (Tot. Employ. ) Presample Mean | 0.153*** | | | 0.153*** | | | 0.172*** | | | 0.171*** | | |
| | (0.028) | | | (0.028) | | | (0.020) | | | (0.020) | | |
| log (Perm. Employ. ) Presample Mean | | 0.168*** | | | 0.169*** | | | 0.195*** | | | 0.193*** | |
| | | (0.027) | | | (0.027) | | | (0.017) | | | (0.017) | |
| log (Temp. Employ. ) Presample Mean | | | 0.313*** | | | 0.313*** | | | 0.283*** | | | 0.280*** |
| | | | (0.019) | | | (0.019) | | | (0.018) | | | (0.017) |
| Lambda cont. operation | -0.319*** | -0.430*** | -1.075*** | -0.309*** | -0.420*** | -1.061*** | -0.236*** | -0.364*** | -0.948*** | -0.173*** | -0.300*** | -0.730*** |
| | (0.046) | (0.055) | (0.182) | (0.046) | (0.056) | (0.182) | (0.047) | (0.059) | (0.213) | (0.052) | (0.066) | (0.242) |
| Constant | 0.084*** | 0.223*** | -0.482*** | 0.090*** | 0.228*** | -0.475*** | -0.433*** | -0.298*** | -0.841*** | -0.436*** | -0.290*** | -0.808*** |
| | (0.030) | (0.035) | (0.130) | (0.029) | (0.034) | (0.130) | (0.070) | (0.078) | (0.251) | (0.070) | (0.078) | (0.251) |
| N observations | 18,286 | 18,286 | 18,286 | 18,286 | 18,286 | 18,286 | 18,117 | 18,117 | 18,117 | 18,117 | 18,117 | 18,117 |
| N firms | 2,723 | 2,723 | 2,723 | 2,723 | 2,723 | 2,723 | 2,795 | 2,795 | 2,795 | 2,795 | 2,795 | 2,795 |

*Note:* All estimations include industry and time dummies. Since all regressions include the estimated lambda term, we provide block-bootstrapped standard errors in parentheses. ***, **, and * mean significant at the 1 percent, 5 percent, and 10 percent level, respectively.

## 1.5. Concluding remarks

Spain, among the southern European countries, is a relevant case study to analyse the effect of SMEs export participation on their resilience to job destruction generated by recessive periods associated with domestic demand. During the Great Recession, it was the only country in this group that simultaneously suffered a sharp drop in GDP and domestic demand, a sharp rise in the unemployment rate, and a significant take-off in its exports and in the participation of SMEs in this activity. Furthermore, a high number of temporary workers, typically considered more vulnerable and precarious, characterised the composition of employment in Spain at the beginning of the recession. For all these reasons, in this work we were not only interested in analysing the link between SMEs export participation and their level of employment in recessive periods, but also in differentiating its effects for workers with temporary or permanent contracts.

Using a firm-level panel dataset for manufacturing SMEs provided by the Spanish Survey on Business Strategies (ESEE) for the period 2000-2014, we obtain that exporting SMEs show greater resilience in terms of employment in a period of recession than non-exporting SMEs. Furthermore, this compensatory effect of exports on employment works in favor of permanent workers, being statistically insignificant for temporary workers. This implies that the ratio of permanent to temporary workers increases for SMEs during recessive periods. In addition, exporting increases SMEs survival chances. Otherwise, SMEs survival is negatively affected by financial constraints, production costs and a recessive demand. Finally, we provide further evidence supporting that SMEs participation in exports also obeys to a reaction to the fall in domestic demand (the so-called “venting out” hypothesis). Likewise, we confirm the theoretical prediction in Almunia et al. (2021), which states that firms with a higher production capacity used can

benefit the most by adapting in the short term to the fall in domestic demand. These firms can move downward in their marginal cost curve by adjusting their labour input. With this they can lower prices, consequently increase their competitiveness, and therefore, export and increase their profits.

We can extract from this chapter several policy recommendations for SMEs. Given that, on the one hand, exporting in recessive periods has helped SMEs to offset the negative effect of the downturn *per se* in their levels of employment and, on the other hand, it has also been a good strategy for SMEs survival, public policies should facilitate this activity among SMEs. For instance, according to our results for the export equation, this can be done by promoting innovation activities among SMEs, alleviating their financial constraints, facilitating their access to external markets, or increasing their competitiveness by promoting productivity enhancing policies. These policies would not only help offset the job losses suffered by SMEs in recessive periods, but also, according to our results, would favor permanent employment over temporary employment, which can help alleviating instability and precariousness in the Spanish labour market.

Our study contributes to the European needs of boosting SMEs performance. Interreg Europe presents in its agenda the necessity of implementing better policies in order to boost and support SMEs, since the competitiveness of these firms is at the forefront of their objectives (Interreg Europe, 2021). In order to achieve this increase in competitiveness, the Horizon 2030 of the European Commission also highlights the necessity of promoting the internationalisation of SMEs (Bichisao et al., 2019). Hence, our chapter sheds light on how this internationalisation of SMEs, more precisely through exporting, can help offset the shocks on employment suffered during downturns, gaining this way in competitiveness.

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# APPENDIX 1

Table A1.1. Variables description.

| Variables | Description |
|---|---|
| *Export* | Dummy variable taking value 1 if the firm exports and 0 otherwise. |
| *Total Employment* | Number of workers |
| *Permanent Employment* | Number of permanent workers |
| *Temporary Employment* | Number of temporary workers |
| $Innov^{product}$ | Dummy variable taking value 1 if the firm has introduced a product innovation and 0 otherwise |
| $Innov^{process}$ | Dummy variable taking value 1 if the firm has introduced a process innovation and 0 otherwise |
| *Recessive Demand* | Dummy variable taking value 1 if the index of market dynamism is between 0 and 35 (indicating a recessive demand) and 0 if the index is between 36 and 100 (indicating a stable or expansive demand). |
| *Recessive Index* | It is based on the index of market dynamism that ranges between 0 and 100, whose direction has been reversed so that the closer to 100, the more recessive the market is. |
| *Financial Restrictions* | Deviation of the firm's financial cost of long-term loans with financial institutions with respect to the average cost paid by other firms in the same year. |
| *Growth_Domestic_Sales* | Growth of domestic sales, expressed on a per unit basis. |
| *Capacity utilization* | Percentage of the productive capacity used by the firm. |
| *High capac. utiliz.* | Dummy variable taking value 1 if the productive capacity used is 80% or higher and 0 otherwise. |
| *Average_Wage* | Average salary per worker (in euros). |
| *Intermediates price change (%)* | Change in the prices of intermediate inputs (in percentage). |
| *LabProd* | Labour productivity measured as output per worker (in euros). |
| *rat_temporary* | Temporary employment over total employment, expressed on a per unit basis. |
| *Foreign participation* | Dummy variable taking value 1 if the firm has foreign capital participation and 0 otherwise. |
| *Age* | Firm's age in years. |

Table A1.2. Probit estimates for SMEs continuation in operation.

| Variables | (1) $Continuation\ in\ operation_t$ (annual data) | (2) $Continuation\ in\ operation_t$ (3-year rolling average) |
|---|---|---|
| $Export_{t-1}$ | 0.093*** | 0.067† |
| | (0.035) | (0.042) |
| $Innov_{t-1}^{Product}$ | 0.098** | 0.097† |
| | (0.048) | (0.065) |
| $Innov_{t-1}^{Process}$ | 0.234*** | 0.255*** |
| | (0.040) | (0.057) |
| $Financial\_Restrictions_{t-1}$ | -0.039** | -0.072** |
| | (0.016) | (0.029) |
| $Recessive\_Index_{t-1}$ | -0.002*** | -0.003*** |
| | (0.001) | (0.001) |
| log $(Average\_wage_{t-1})$ | -0.441*** | -0.416*** |
| | (0.057) | (0.071) |
| $Intermediates\ price\ change(\%)_{t-1,t}$ | -0.003** | -0.007** |
| | (0.002) | (0.003) |
| log $(LabProd)_{t-1}$ | 0.154*** | 0.185*** |
| | (0.028) | (0.032) |
| $Ratio\ temporary\ employment_0$ | -0.170** | -0.017 |
| | (0.066) | (0.076) |
| $Capacity\ utilization_{t-1}$ | 0.007*** | 0.007*** |
| | (0.001) | (0.001) |
| $Foreign\ participation_{t-1}$ | -0.129** | -0.192*** |
| | (0.058) | (0.067) |
| $Medium_{t-1}$ | -0.007 | -0.062 |
| | (0.038) | (0.046) |
| log $(Age_{t-1})$ | 0.070*** | 0.167*** |
| | (0.020) | (0.024) |
| Constant | 8.550*** | 7.494*** |
| | (0.557) | (0.637) |
| Proportion of total variance contributed by the panel level variance | 9.32e-07 (0.038) | 0.047 (0.035) |
| Log pseudo-likelihood | -4178.8394 | -3581.4707 |
| $N\ observations$ | 19,866 | 15,368 |
| $N\ firms$ | 2,824 | 2,477 |

*Note*. All estimations include industry and time dummies. Clustered robust standard errors are in parentheses. ***, **, and * mean significant at the 1 percent, 5 percent, and 10 percent level, respectively. † means slightly above 10 percent level (11% for the export variable and 13% for the Product innovation variable). The dataset used in column 2 is constructed calculating three-year rolling averages of all the variables for each firm. Since the dependent variable is a binary variable 0/1 and we are estimating a *Probit* model, the rolling average of the dependent variable is set to 0 when in a particular interval the firm dies.

# Chapter 2. Misallocation of intermediate inputs and Global Value Chains

## 2.1. Introduction and motivation

Misallocation of production factors occurs when available resources are inefficiently distributed among firms. This inefficiency hinders aggregate output growth. Since it results from the reallocation of production factors without varying the input amount, it has direct implications for Total Factor Productivity (TFP) growth. Therefore, the study of factor misallocation is relevant not only due to its implications for aggregate output but also for TFP growth. In the presence of input misallocation, more efficient firms tend to operate below their optimal size, while less efficient firms tend to operate beyond their optimal size.

The related literature has measured the allocative efficiency of production factors in two different ways. The first method, as described in Hsieh and Klenow (2009), is based on the within-industry dispersion in the marginal revenue products (MRPs) of inputs. Higher dispersion is expected to be associated with more barriers, distortions, or frictions that impede the efficient allocation of inputs, resulting in a loss in aggregate output and productivity. If such frictions did not exist, firms in the same industry would equalise the MRPs of each input. In this branch of the literature, this measure is based on revenue production functions, employing industry deflators. The second method is a firm-level misallocation measure proposed by Petrin and Sivadasan (2013). In this case, a firm's misallocation of inputs is measured by the absolute value of the gap between the value of the marginal product (VMP) and the marginal cost of an input. Unlike MRPs, VMPs of inputs are calculated based on quantity-based production functions. Petrin and Sivadasan (2013) demonstrate that this gap corresponds to the change in aggregate output that would occur if a firm were to shift the use of that input in the efficient direction by

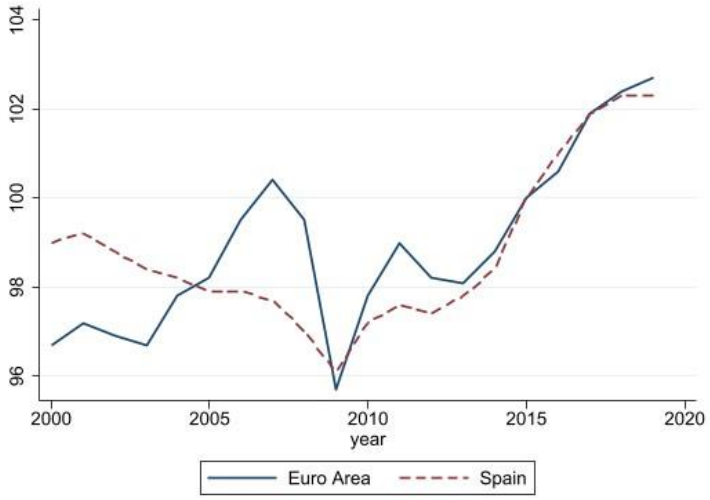
one unit while holding aggregate input use constant. An efficient direction means reallocating input units from lower to higher marginal product firms. In the absence of frictions, firms will reach their optimal level of hiring for a particular input, and consequently, the VMP for the input will equalise its marginal cost.

Our chapter focuses on firms' misallocation of intermediate inputs and its relationship with their participation in global value chains (GVCs). Our primary hypothesis is that firms engaged in GVCs, which involve international trade in intermediates and foreign sourcing, are better equipped to navigate frictions within intermediate input markets compared to firms sourcing intermediates exclusively domestically. To test this hypothesis, we use the less commonly explored firm-level measures of factor misallocation proposed by Petrin and Sivadasan (2013), using panel data from a representative sample of Spanish manufacturing firms (Survey on Business Strategies, ESEE). But what motivates our focus on the Spanish case and intermediate inputs?

To address this question, let's first examine Spain's Total Factor Productivity (TFP) trends. Figure 2.1 illustrates TFP trends for both Spain and the Euro area, using data sourced from official statistics (AMECO), starting from 2000. Notably, Spanish TFP experienced a decline and deceleration until 2009. To delve deeper into this behaviour, we can turn to two recent and insightful papers that specifically focus on the Spanish case, covering the pre-Great Recession years. The papers are Gopinath et al. (2017) and García-Santana et al. (2020). It is worth noting that their data sources differ from ours as they use data from Orbis-Amadeus or from the Bank of Spain, respectively. The Bank of Spain Micro Dataset corresponds to the dataset used in Almunia et al. (2018). Both papers start with firm-level data to construct industry-level measures of production factor misallocation, such as the within-industry dispersion of MRPs of inputs. Their time spans

differ from ours (1999-2012 and 2000-2007, respectively, whereas our study is more interested in explaining the TFP recovery period), and both focus on the evolution of capital and labour misallocation. Unlike us, they estimate Value Added (gross output minus intermediate inputs) production functions rather than Gross Output production functions. Both studies reveal a higher dispersion of the MRP of capital compared to labour and a significant increase in the dispersion of the MRP of capital, while the dispersion of the MRP of labour remains stable during the analysed period. Consequently, both papers suggest that the evolution of allocative inefficiency in capital allocation is likely responsible for the decline in the aggregate TFP observed before the Great Recession. The stability in labour allocation efficiency cannot explain the observed pattern in TFP. In addition, these studies explore potential distortions affecting capital input markets and find that factors such as the excess availability of credit and low interest rates (Gopinath et al., 2017) or the deterioration of institutional quality (García-Santana et al., 2020) play significant causal roles in explaining capital misallocation.

Figure 2.1. Evolution of TFP for the Euro area and Spain




Notes: (i) Source: AMECO (ii) We normalise the TFP to base 100 in the year 2015.

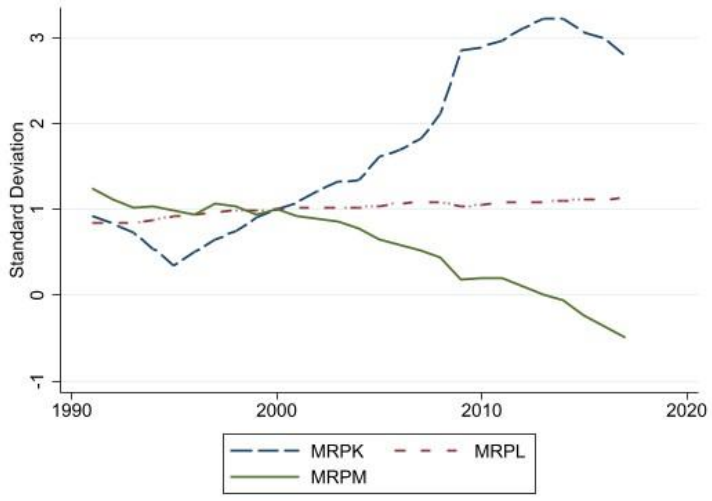
Figure 2.1 also illustrates that the decline in TFP began to reverse after 2009. This observation leads us to question whether there has been a corresponding evolution in the allocative efficiency of production factors that aligns with the observed TFP growth pattern since 2009. It is noteworthy that our chapter uses data for the Spanish economy up to 2017. To address this inquiry and facilitate comparisons with prior studies that have assessed misallocation at the industry-year level in Spain by examining the dispersion of MRPs of capital and labour (such as Gopinath et al., 2017, for the period 1999-2012, and García-Santana et al., 2020, for the period 2000-2007), we present in Figure 2.2 the evolution of the dispersion of logged returns for capital, labour, and intermediate inputs. Dispersion measures are calculated using our distinct Spanish database (the ESEE), while previous studies relied on Orbis-Amadeus or data from the Bank of Spain. This does not only allow us to assess whether our database reveals a similar trend in the evolution of capital and labour misallocation as observed in prior research on the Spanish economy but also enables us to investigate whether there is a specific input whose behaviour aligns with the observed recovery of TFP. We add to these previous papers the evolution of the same type of misallocation measure for intermediate inputs, which are the key inputs of interest for us in this chapter. First, we calculate dispersion measures at the industry level as the standard deviation of weighted input returns at the firm level within two-digit manufacturing industries (NACE classification) for each year.[24] Second, for each year, the aggregate measures for the entire manufacturing industry, as shown in Figure 2.2, are derived by weighting those obtained from individual industries based on their respective shares in total manufacturing production.[25] Using a different dataset and a distinct time

[24] When determining within-industry weights, we take into consideration the different representation of large and small firms in the ESEE dataset.

[25] We calculate a time-invariant weight for each industry based on its average share in manufacturing production. This approach ensures that the evolution of dispersion measures reflects only the within-industry variation of MRPs over time.

interval—the ESEE covering the period from 1991 to 2017—we have identified an evolution in misallocation measures of capital and labour similar to previous research. Specifically, there is an increasing dispersion trend for capital (with a deceleration observed since 2009) and a stable pattern for labour. However, notably, since 1991 and particularly since 2000, we have observed a significant reduction in the dispersion of MRPs of intermediate inputs, indicating improved efficiency in the allocation of this specific type of input. This finding, coupled with the positive trend in TFP growth since 2009 illustrated in Figure 2.1, suggests that the deceleration in capital misallocation and, more significantly, the acceleration of better allocation of intermediate inputs, may be contributing to the enhancement in TFP performance.

Figure 2.2. Evolution of MRPK, MRPL and MRPM dispersions.




Note: (i) Source: Own elaboration with firm-level data from ESEE. (ii) MRPK, MRPL and MRPM are expressed in logarithms. (iii) We normalise the MRPs to base 1 in the year 2000.

Figure 2.2 reveals another significant finding: an uneven evolution in the dispersions of MRPs for the three inputs under examination. Specifically, we observe that the dispersion of MRPs for capital increases, whereas the dispersion of MRPs for intermediate inputs is decreasing, and the dispersion for labour remains stable. These

contrasting patterns suggest that a common shock is not driving the misallocation behaviour across all three inputs. Instead, it indicates a substantial role played by specific frictions within each input market (Petrin and Sivadasan, 2013; Gopinath et al., 2017). Previous studies have focused on capital and labour inputs, revealing evidence that specific frictions within these markets distort resource allocation. For example, Gopinath et al. (2017) concentrated on capital market frictions, particularly those related to access to credit. In a similar vein, García-Santana et al. (2020) found that allocative efficiency suffered when institutional quality declined. However, when it comes to labour market frictions causing labour misallocation, both theoretical and empirical literature emphasise firing costs (Hopenhayn and Rogerson, 1993; Petrin and Sivadasan, 2013, using Chilean data; Da-Rocha et al., 2019; García-Santana et al., 2020, using Spanish data; Alpysbayeva and Vanormelingen, 2022, using Belgian data).

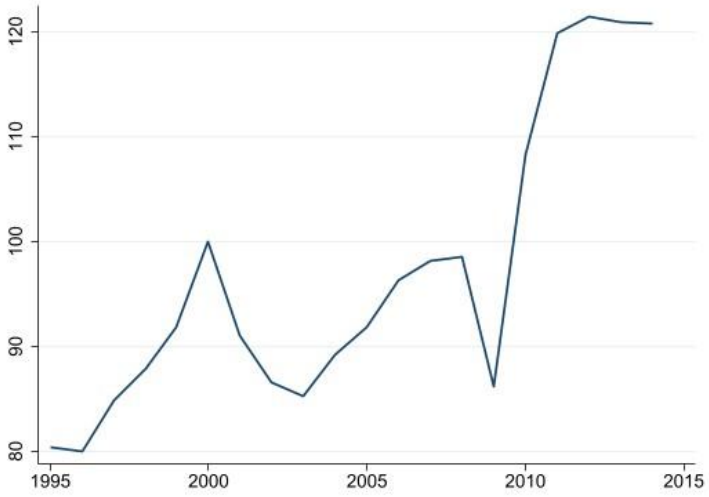
Conversely, given the central focus of this chapter on the misallocation of intermediate inputs, our working hypothesis posits that increased participation in GVCs might be a key factor contributing to a more efficient allocation of these inputs. To the best of our knowledge, this particular aspect remains unexplored in the existing literature. GVCs are intricately linked with trade of intermediate goods (Antràs, 2020). Consequently, firms engaged in GVCs enjoy distinct advantages when it comes to accessing intermediate inputs (Halpern et al., 2015; Máñez et al., 2020; Máñez Castillejo et al., 2020). Unlike those reliant solely on domestic sourcing, these firms are not constrained by geographical boundaries, affording them greater flexibility in adapting to market frictions that may arise in specific markets.

But has Spain increased its participation in GVCs? In Figure 2.3, we plot the evolution of the Foreign Value Added (FVA) indicator of GVC participation for the Spanish economy. FVA is one of the main indicators of GVC participation, representing

the content of intermediate imports embodied in exports. The data are sourced from Borin and Mancini's (2019) novel dataset on GVC participation measures, based on the World Input-Output Database (WIOD). Since 2003, there has been a general increase in the Spanish economy's participation in GVCs, with the sole exception of the trade debacle from 2008 to 2009 due to the initial effects of the Great Recession on trade. This growth in Spain's GVC participation may underlie the observed improvement in the allocative efficiency of intermediate inputs, as shown in Figure 2.2. Additionally, this trend may also be reflected in the enhanced evolution of the aggregate productivity level of the Spanish economy, particularly from 2009, as illustrated in Figure 2.1.

At this point, we hope to have sufficiently motivated our interest in the study of the misallocation of intermediate inputs, its connection with GVCs and the importance of having chosen the Spanish case as a case study for our work. Furthermore, there are some figures that also underscore the significance of intermediate goods in a broader context. Their importance in world trade is evident and continuously increasing. Approximately 60% of the goods imported by EU countries consist of intermediate inputs. Moreover, they account for about half of their exports. Interestingly, Spain ranks among the top 10 EU countries in terms of imports of intermediate products. In fact, these imports of intermediate products have nearly doubled since 2000 (European Commission, 2022).

Figure 2.3. FVA in Spain.




Notes: (i) Source: World Input-Output Database (WIOD). (ii) We normalise FVA to base 100 in the year 2000.

Our contribution to the literature is many-sided. Firstly, in addition to using measures of dispersion of MRPs of inputs for descriptive purposes and for comparison with previous work in Spain and prior literature using more aggregated measures of production factors' misallocation, we measure misallocation at the firm-level following the newer methodology proposed by Petrin and Sivadasan (2013). Secondly, there are significant differences between our work and most previous papers. Previous literature has predominantly concentrated on examining the misallocation of capital and labour, often overlooking the misallocation of intermediate inputs. Thirdly, in terms of measuring misallocation, we approach a quantity-based production function by using firm-level deflators that can be constructed from our database. This distinction is crucial because using industry deflators may introduce a bias in the estimates of input elasticities in the production function. This bias may lead to attributing to misallocation something that is a failure to control for price dispersion within the industry. Lastly, and of particular

relevance to our study, we focus on investigating the misallocation of intermediates and its causal relationship with firms' participation in Global Value Chains (GVCs).

The results of the chapter reveal that firms' participation in GVCs helps alleviate misallocation of intermediates. This is firstly motivated by a descriptive graphical analysis and confirmed using various estimation methods, including Ordinary Least Squares (OLS), two-way fixed effects (TWFE), and a staggered difference-in-differences (DiD) estimation procedure (Callaway and Sant'Anna, 2021) to establish causality. The final approach enables us to examine the impact of firm participation in GVCs using dichotomous indicators. Additionally, we employ a DiD approach with a continuous treatment intensity, exploiting the emergence and expansion of fibre-optic-based ICT technology in Spain. This approach allows us to use continuous measures of firms' GVC participation to assess their exposure to a shock that facilitates GVC operations. Our conclusions are further strengthened by robustness checks. In terms of policy implications, we show a source of allocative efficiency of intermediate inputs that can help us understand the evolution of Spanish TFP and be useful in efforts to improve it.

The chapter is organised as follows: Section 2.2 briefly reviews the relevant literature. In Section 2.3, we present the methodology for measuring allocative inefficiency and GVC participation. Section 2.4 focuses on the data and provides descriptive statistics. In Section 2.5, we elaborate on the estimation process and present the main results. Section 2.6 consists of robustness checks, and finally, in Section 2.7, we draw our conclusions.

## 2.2. Literature Review.

The literature has examined allocative efficiency of production factors in two ways. The most traditional approach focuses on the within-industry dispersion of logged MRPs

of inputs as a measure of misallocation at the industry-year level. In this literature (originating from Hsieh and Klenow, 2009), the dispersion of MRPs is considered indicative of input misallocation since it would be efficient to reallocate inputs from firms with low to high MRP until MRPs are equalised across firms. Hsieh and Klenow (2009) employed this method to assess the misallocation of labour and capital in Chinese manufacturing plants from 1998 to 2005 and Indian manufacturing plants from 1987 to 1994, comparing them to the United States data from 1977, 1987, and 1997. More recently, Petrin and Sivadasan (2013) proposed a measure of firm-level misallocation based on unrealised increases in aggregate productivity growth resulting from a firm shifting the use of a specific input in the efficient direction by one unit. Their measure calculates the difference between the marginal product and the marginal cost of that input. In their paper, they demonstrate that this gap precisely quantifies the change in aggregate output that would occur if a firm were to shift the use of that input in the efficient direction by one unit while keeping aggregate input use constant. An 'efficient direction' in this context refers to reallocating input units from firms with a lower marginal product to those with a higher marginal product. In their study, they mainly focus on explaining labour gaps in Chilean manufacturing plants during the period 1982-1994, with a particular emphasis on firing costs.

Following the seminal works and theoretical advancements on misallocation by Hsieh and Klenow (2009) and Petrin and Sivadasan (2013), subsequent empirical research has predominantly concentrated on examining the dispersion of MRPs associated with inputs. This research particularly emphasises the MRP of capital and the distortions observed within this market. Among these studies, some have delved into the misallocation of production factors within Spain, with one notable study being conducted by Gopinath et al. (2017). They use the ORBIS-AMADEUS dataset for manufacturing

over the period 1999-2012. The paper is focused on capital allocation since they find in their data that during this period, there is a significant increase in the dispersion of the MRP of capital but a stable dispersion of the MRP of labour. Consequently, this paper presents evidence of a rise in capital misallocation, which can be attributed to access to credit. It is well-known that in imperfect capital markets, an oversupply of credit may flow towards less efficient firms. As they noted, during their study period, Spain's entry into the EMU led to a decrease in real interest rates, accompanied by significant capital inflows and favourable borrowing conditions. In addition, this paper provides evidence that the low productivity growth in Spain and South Europe during this period is accompanied by a significant increase in capital misallocation.[26]

Another relevant paper trying to explain the macroeconomic productivity slowdown in Spain between 2000-2007 is García-Santana et al. (2020). The authors show that during the same period, the economy experienced an increase in misallocation attributed to a decline in institutional quality. They contend that this rise in misallocation was responsible for the negative growth in TFP. Employing measures of within-sector allocative inefficiency, such as examining the dispersion of firm-logged MRPs of both capital and labour, the authors find that allocative efficiency deteriorates with a decline in institutional quality. This deterioration is more pronounced in industries where connections with public officials play a crucial role in success. These industries are the ones suffering more significant productivity losses due to misallocation. They use the BdE Micro Dataset from Almunia et al. (2018), which includes firms from all sectors, and

[26] Añón Higón et al. (2022), using AMADEUS data spanning the period 2003-2014 in the European Union, also present empirical evidence supporting the existence of capital misallocation during the pre-Great Recession period in Europe—a period characterised by excessive and sometimes indiscriminate credit provision. Capital appears to have been allocated to the least productive firms during this period. In contrast, the implementation of stricter regulations on credit provision during the Great Recession might have alleviated the earlier capital misallocation by directing funds towards more productive firms. Notably, the paper did not find evidence of capital misallocation during this latter period.

observe a larger dispersion of the marginal revenue product of capital than of labour, aligning with findings from Gopinath et al. (2017).

Empirical research within the second strand of literature, which focuses on evaluating firm-level misallocation by comparing marginal products and marginal input costs (following the theoretical developments of Petrin and Sivadasan, 2013), remains relatively scarce and recent. One such paper is Fontagné and Santoni (2019). They estimate the degree of firm-level input allocation for French manufacturing firms over the period 1993-2007. Their specific emphasis is on labour gaps and how population density influences labour market matches. Their analysis involves estimating Value Added production functions. They reveal that firm misallocation is lower in denser areas, which they interpret as a consequence of improved labour market matching mechanisms in these areas (i.e., fewer frictions). They refer to this as agglomeration economies associated with better access to a variety of inputs. Another recent study is Alpysbayeva and Vanormelingen (2022). They use the universe of Belgian private firms for the period 1996-2017. Their analysis also estimates Value Added production functions. They estimate the impact of labour market rigidities on labour misallocation (measured by labour gaps). To accomplish this, they exploit a change in employment protection policy in Belgium, which increased protection for blue-collar workers relative to white-collar workers. They show that this policy change reduced allocative efficiency for blue-collar workers compared to their white-collar counterparts.

Therefore, the literature, whether from an aggregate perspective or a firm-level point of view, has primarily focused on studying capital or labour misallocation and delving into the underlying frictions associated with them. However, our interest lies in exploring the misallocation of intermediate inputs. A few studies have highlighted the potential for misallocation in the utilisation of intermediate inputs. For instance, varying

contract enforcement strength may influence plants' input choices (Boehm and Oberfield, 2020), and location may play a crucial role in shaping market access—a factor that subsequently impacts the cost and utilisation of intermediate inputs (Aggarwal et al., 2022; Singer, 2019).[27] In this chapter, we explicitly consider the potential misallocation of intermediate inputs and delve into one specific factor. Particularly, we posit that GVC participation may help alleviate misallocation in intermediates by facilitating access to intermediate input markets and in a more flexible manner. There is not only a scarcity of studies on the misallocation of intermediate inputs but also a lack of research on its underlying causes.

## 2.3. Methodology

### 2.3.1. Measuring misallocation.

Petrin and Sivadasan (2013) propose a firm-level measure of misallocation that uses production data to estimate the differences between the value of the marginal product of an input and its marginal cost. Estimating the marginal products of inputs requires the estimation of production functions. We estimate a Cobb-Douglas production function following Wooldridge (2009). The function is written as:

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \eta_{it} \quad (2.1)$$

where $i$ indexes firms and $t$ indexes time, $q_{it}$ is the log of the real output, $l_{it}$ is the log of the number of total hours worked in the firm, $k_{it}$ is the log of the real capital stock

[27] Singer (2019) develops and estimates a structural model to study welfare losses from input misallocation using plant-level data from the Indian steel industry. Interestingly, the paper shows that welfare losses due to misallocation in material input markets are larger than those due to labour misallocation (it obtains a larger misallocation in material inputs than in labour) and that better access to relevant input suppliers decreases material input market distortions and hence material misallocation. However, this paper focuses only on domestic sourcing and ignores international sourcing. The reason for ignoring international sourcing is that, in the data, the share of imported materials in total materials is only around 2% for this industry.

and $m_{it}$ is the log of the real intermediate inputs. As for the unobservables, $\omega_{it}$ is the firm productivity (not observed by the econometrician but observable or predictable by firms) and $\eta_{it}$ is an i.i.d. productivity shock that is neither observed nor predictable by the firm.[28] A central advantage of our dataset is that it is possible to build firm-level deflators for output and intermediate inputs. These firm-level deflators allow us to work with a 'quantity-based' production function rather than a 'revenue-based' one, where nominal variables are adjusted using industry deflators.[29,30]

We employ the Gross Output approach in estimating the production function as our focus is on measuring the output's elasticity concerning intermediate inputs. This method involves establishing a functional relationship between a firm's output measure and its capital, labour, and intermediate inputs. In the existing body of literature, the prevalent approach has been to employ a 'value-added' production function. Nevertheless, even in studies exclusively focused on labour and capital misallocation, using a 'value-added' production function could potentially underestimate the genuine extent of misallocation due to frictions in intermediate input markets (Wang, 2022). In essence, the estimates of misallocation could be biased in the presence of heterogeneity in frictions associated with intermediate input markets among firms within the industry, as these frictions would persist in the 'value-added' measure. We posit that this heterogeneity can be driven by differences in accessibility and adaptability to shocks in those markets among firms

[28] To obtain estimates of input elasticities, we follow Wooldridge (2009) that modifies the Levinsohn and Petrin (2003) approach to address the problem of the simultaneous determination of inputs and productivity. We refer the reader to his paper for details of the estimation process.

[29] The labour input is already measured in real terms. Real capital is derived by deflating current replacement values of capital by the price index of investment. Specifically, the price index of investment is obtained as the equipment goods component of the index of industry prices published by the Spanish National Institute of Statistics.

[30] The detailed definition of the variables utilised in estimating the production function and those involved in the misallocation measures can be found in Table A2.1 in Appendix 2.

participating in GVCs compared to those not participating. Therefore, the use of the Gross Output approach enables the derivation of more accurate measures of misallocation.

Our estimation of gross output production functions is performed separately for each of the 20 two-digit manufacturing sectors in accordance with the NACE classification. Consequently, elasticities concerning inputs vary at the two-digit industry level, yielding reasonable estimates.[31] While our primary findings in the chapter rely on Cobb-Douglas production functions, we also present results using Translog production functions in a dedicated section for robustness checks. Translog production functions offer greater flexibility because they allow the output elasticities of inputs to vary among firms within the industry and over time. However, this flexibility may come at the cost of increased multicollinearity among regressors, potentially affecting identification, or exacerbating potential measurement errors in firms' responses regarding output and input amounts. Still, we are interested in verifying whether our main results hold when using Translog production functions, as this would provide further confirmation that our measures accurately capture varying degrees of misallocation among firms within the same industry. Translog production functions, with their ability to accommodate firm-specific output elasticities for inputs, help account for the fact that firms within the same industry may also exhibit heterogeneity in terms of technological differences.

Given the estimates of the elasticities of output with respect to individual inputs from (2.1), the marginal products of inputs are given by:

[31] The average elasticity for materials is 0.518, for labour 0.22 and for capital 0.105. Table A2.2 in Appendix 2 shows the inputs coefficients by sector.

$$\frac{\partial Q_{it}}{\partial L_{it}} = \beta_l \cdot \frac{Q_{it}}{L_{it}},$$
$$\frac{\partial Q_{it}}{\partial K_{it}} = \beta_k \cdot \frac{Q_{it}}{K_{it}}, \qquad (2.2)$$
$$\frac{\partial Q_{it}}{\partial M_{it}} = \beta_m \cdot \frac{Q_{it}}{M_{it}},$$

where firm-level output and inputs are in levels rather than logarithms. Multiplying the marginal products of inputs by the firm's output price gives the VMP of a given input. Furthermore, we calculate the marginal costs for inputs by utilising the average costs per unit of input, with $w_{it}$ representing the wage per unit of labour, $r_{it}$ the cost per unit of capital, and $p_{it}^m$ the price per unit of intermediate input.[32] Hence, the absolute difference between the VMP and the cost per unit of input for each input is:[33]

$$G_{it}^l = \left| VMP_{it}^l - w_{it} \right|,$$
$$G_{it}^k = \left| VMP_{it}^k - r_{it} \right|, \qquad (2.3)$$
$$G_{it}^m = \left| VMP_{it}^m - P_{it}^m \right|,$$

From Lemma 1 in Petrin and Sivadasan (2013) "the average absolute gap for an input in any period is an approximate measure of the potential gain in productivity from a unit adjustment of that input in the optimal direction". It represents the average net increase in aggregate output achieved by shifting one unit of input from a firm with a negative gap to a firm with a positive gap. Figure 2.4, sourced from Petrin and Sivadasan (2013), illustrates the case of a firm with a positive gap between the VMP of labour and the wage rate. When this gap is eliminated, the firm can achieve its optimal hiring level

[32] Previous literature examining misallocation has commonly employed average cost as an approximation for marginal cost. Examples include studies by Petrin and Sivadasan (2013), Fontagné and Santoni (2019), and Alpysbayeva and Vanormelingen (2022), among others.

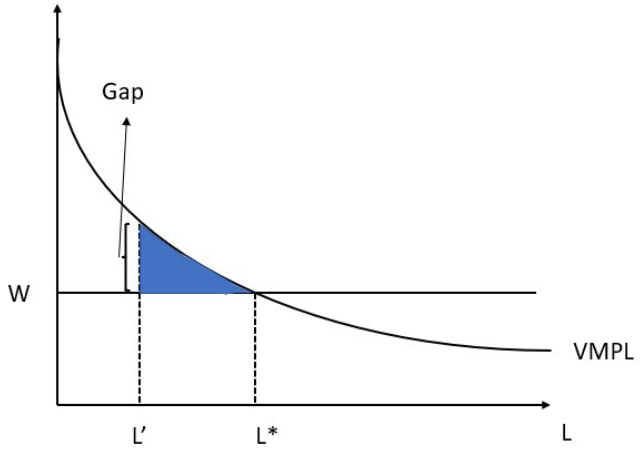
[33] Whenever necessary in the chapter to make the gap comparable over time, we use the absolute real gap by deflating the nominal value with the Industry Price Index provided by the Spanish National Statistics Institute.

at $L^*$, resulting in an allocative efficiency gain that increases output by the shaded area. This example of a firm with a positive gap serves to illustrate that resource misallocation often leads to the most efficient firms operating below their optimal size. Conversely, firms with a negative gap may experience the opposite effect. The existence of input markets' frictions can hinder firms from adjusting their input choices to reach their optimal size.

Finally, it is worth mentioning that prior to the work of Petrin and Sivadasan (2013), or even considerably later, most of the literature on misallocation focused on the within-industry dispersion of logged MRPs of inputs, used as a measure of misallocation at the industry-year level. The MRPs of inputs are the equivalent to the VMPs of inputs when instead of estimating the elasticities of output with respect to individual inputs from a "quantity-based" production function they are estimated from a "revenue-based" production function. In this case, input elasticities in the production function are $\beta'_j = \beta_j[1+(1/\varepsilon)]$, were $\varepsilon$ is the elasticity of demand and $j=l$, $k$ or $m$. With "revenue-based" production functions, production function elasticities are consistent if inputs are not correlated with the deviation of the firm-level price from the industry price index (otherwise, there can be a bias, De Loecker, 2011). Input elasticities $\beta'_j$ are "revenue" elasticities that in the presence of markups are estimated as lower bounds for the true elasticities $\beta_j$. In this literature, within-industry dispersion in the MRPs is considered to be indicative of inputs misallocation, since it would be efficient to reallocate inputs from firms with low to high MRP until MRPs are equalised across firms. As we work with a "quantity-based" production function we get closer to the concept of misallocation as something generated from frictions in input markets, since with quantity-based output and input measures misallocation is "purged of substantial variation in markups across firms" (De Loecker et al., 2016). This is reinforced by the evolution of the dispersion of

the MRP of the inputs as illustrated in Figure 2.2. As the dispersion of the three considered inputs evolves differently—increasing for capital, decreasing for intermediate inputs, and remaining stable for labour—it is improbable that there are distortions common to all inputs. Rather, it is more plausible that there are input-specific distortions. A common distortion discussed in the literature, expected to impact the dispersions of all inputs, arises from the heterogeneity in price differentials when firm-specific price information is unavailable, and we have to rely on revenue data.

Figure 2.4. Allocative efficiency gains from eliminating a positive gap.




Source: Figure 1 in Petrin and Sivadasan (2013).

### 2.3.2. Measuring GVCs participation.

Given our main working hypothesis, which postulates that firms participating in GVCs can alleviate sourcing constraints by gaining greater access to intermediate inputs through international sourcing—enabling them to navigate and mitigate frictions in intermediate input markets more effectively than firms exclusively sourcing domestically—we now shift our attention to the GVC measures used in this chapter. To identify GVC participation at the firm level, we will employ two measures: Foreign Value Added (FVA) and Indirect Value Added (IVA), representing the backward and forward

integration of firms into GVCs. These measures allow us to discern both the intensive and extensive margins of participation.

FVA is based on foreign value added in exports, which measures imported intermediates embodied in exports. In particular, FVA refers to the value added of inputs that were imported to produce intermediate or final goods that are exported, or in other words, the content of intermediate imports embodied in exports. It is a measure of "Backward integration" and also of "Downstream participation".[34] We can also express it as a dummy variable, thereby identifying the extensive margin of participation in GVCs. In this context, we ascertain whether a firm simultaneously imports intermediate goods and exports goods (either intermediate or final). This dummy variable is commonly referred to as the two-way trader dummy in related literature and can be interpreted as the dichotomised version of FVA.

The GVC participation indicator, IVA, represents the domestic value added contained in intermediates exported to a partner economy, which then re-exports them to a third economy, incorporating them into other products. In simpler terms, it quantifies the domestic value added in inputs sent to third economies for further processing and export through value chains. It is a measure of "Forward integration" and also of "Upstream participation" (World Trade Organization, 2019).[35] It has been argued that constructing a measure of IVA using firm-level data is more challenging than FVA (Antràs, 2020). The difficulty arises because, in enterprise surveys, information regarding whether foreign firms that import our intermediate products subsequently re-export them

[34] FVA is an indicator of the firm's backward integration into the GVC, which also indicates that the firm is closer to the final consumer than its international input suppliers, i.e. it has a more downstream position in the GVC than they do.

[35] IVA is an indicator of the firm's forward integration into the GVC, which also indicates that the firm is further away from the final consumer than its international input importers, i.e. it has a more upstream position in the GVC than they do.

to a third economy as part of other products is rarely available. In fact, we are not aware of any enterprise survey that contains this information. Nevertheless, in a globalised world, we can reasonably assume that firms exporting intermediate inputs are likely to be engaged in 'forward integration' (i.e., they have a positive IVA value). This assumption is grounded in the observation that firms importing intermediates are often also exporters (Gal and Witheridge, 2019; Antràs, 2020; Máñez et al., 2020; Máñez Castillejo et al., 2020). Finally, a dichotomised version of IVA can be created by expressing it as a dummy variable with a value of 1 when a firm exporting intermediates incorporates domestic value added into its exports. This dummy variable will capture whether the firm has a positive IVA value, serving as another extensive margin measure of GVC participation.

While the literature on firm-level GVC measures remains limited, this chapter addresses the issue by calculating FVA and IVA for each firm using data from the ESEE. The scarcity of research focusing on firm-level GVC measures arises from the inherent challenges in accurately computing FVA and IVA with most firm-level databases, which often lack crucial information (Antràs, 2020). Specifically, many firm-level databases either lack information on firm imports or fail to distinguish between imports of intermediate and final goods. This lack of information on imports poses a challenge in calculating one of the two relevant indicators of GVC participation, FVA. In other cases, even if there is information on imports, the absence of a distinction between intermediate and final goods requires an assumption that some are intermediate inputs. Additionally, most firm-level databases, even when containing information on exports, typically do not differentiate between exports of intermediate and final goods, hindering the construction of the other measure of GVC participation, IVA. Due to these restrictions, a frequently employed approach in the literature is the use of a two-way trader dummy variable, identifying firms engaged in both imports and exports without specifying whether the

traded goods are final or intermediate. Consequently, the firm-level literature on GVCs has predominantly emphasised the extensive margin of participation (Shepherd and Stone, 2013; Del Prete et al., 2017; Dovis and Zaki, 2020). In contrast, Calatayud and Rochina Barrachina (2023) take a different approach by utilising indicators for both the extensive and intensive margins of participation in GVCs. In their study, they consider available information on imports of intermediates and also attempt to discern whether firms export intermediates or final goods. Focusing on Sub-Saharan African firms, their research explores the impact of GVC participation on various aspects of firm performance. Fortunately, the firm-level database in our current chapter includes information on imports of intermediates and exports of goods, enabling us to distinguish whether firms export intermediates or final goods. This capability allows us to construct both the intensive margin measures of GVC participation at the firm level (FVA and IVA) and their corresponding dichotomised dummy variables (extensive margin measures).[36]

## 2.4. Data and Descriptives

In this chapter, we use a firm-level panel dataset obtained from the Spanish Survey of Business Strategies (ESEE) for the period 1991-2017. The ESEE is an annual survey, sponsored by the Spanish Ministry of Industry and conducted by the SEPI Foundation, which is representative (by industry and size) of the manufacturing sector in Spain.

As discussed in previous sections, our firm-level measures of inputs misallocation are based on the methodology developed by Petrin and Sivadasan (2013). This approach involves calculating the absolute values of the input gaps between their VMPs and marginal costs. We directly apply this methodology to two inputs of the production function, namely labour and capital, and extend it to accommodate the way in which the

[36] The detailed definitions of the GVCs variables used in our work can be found in Table 2.2 of the next section in the chapter, specifically the Data and Descriptives section.

ESEE survey provides information on prices of intermediate inputs. This extension is necessary because the data in the ESEE allows calculating the prices of labour and capital on a yearly basis (i.e., in levels), while for intermediate inputs, it provides information on its percentual variation over time (from period *t-1* to *t*). Hence, for labour and capital, we calculate both the misallocation measures in levels and their extensions to misallocation measures in growth rates for comparability with the growth rate measure of misallocation for intermediate inputs.

Now, let us explain the type of extension performed mathematically for a generic input in the production function and illustrate it graphically using the graph from Petrin and Sivadasan (2013) for the labour input, which we reproduced in Figure 2.4 above.[37] First of all, it should be noted that the mathematical properties of absolute values mean that the subtraction of two absolute values is not the absolute value of the subtraction. This implies that a good measure of inputs misallocation relying on the percentage change in the gap from $t-1$ to $t$ cannot be obtained by calculating $\left| Variation\left(G_{it,t-1}\right) \right|$, since $\left| Variation\left(G_{it,t-1}\right) \right| \neq \left| ln\left(G_{it}\right) \right| - \left| ln\left(G_{it-1}\right) \right|$. Therefore, taking the absolute value of the percentage change in the gap will yield a misleading measure when classifying firms and assessing their evolution in terms of input misallocation. Instead, for this purpose, we can rely on the growth rate of the gap itself without taking absolute values, as the sign of the variation now becomes important. To start illustrating this point, see Figure 2.5. It is evident that irrespective of whether the initial gap in period $t-1$ is positive or negative, a positive growth rate of the gap from that period to the next (period $t$) unambiguously indicates an increase in input misallocation (i.e., the absolute value of the vertical distance

[37] For this reason, we have chosen the labour input for illustration. However, the same analysis applies to both capital and intermediate inputs.

between the VMP of the input and the input cost increases).[38] In Figure 2.6, we explore the scenario of a negative growth rate of the gap. Here, regardless of whether the initial gap in period *t-1* is positive or negative, a negative growth rate unequivocally signifies a reduction in input misallocation (i.e., the absolute value of the vertical distance between the VMP of the input and the input cost decreases), as long as $\left| \textit{Variation}\left(G_{it,t-1}\right) \right| < 1$ (or <100 if working with percentages).[39] Under this condition, Figure 2.6 illustrates that the firm moves closer in period *t* to the optimal point (closer to a zero gap) without changing the sign of the gap it had in period *t-1*. Differently, we can have a situation where a firm surpasses the optimal point (the zero gap). In other words, a firm that had a positive (negative) gap in *t-1* may have a negative (positive) gap in *t*. In such cases, we cannot be sure whether misallocation has decreased or increased, and this uncertainty emerges when $\textit{Variation}\left(G_{it,t-1}\right) < 0$ and $\left| \textit{Variation}\left(G_{it,t-1}\right) \right| > 1$ (or >100 if working with percentages).[40] Thus, to be conservative and to have clean and consistent results, we will

---

[38] Mathematical proof with $\textit{Variation}\left(G_{it,t-1}\right) > 0$: (i) If $G_{it-1} > 0$ necessarily implies that $G_{it} > G_{it-1}$, since $\textit{Variation}\left(G_{it,t-1}\right) = \left[\left(G_{it} - G_{it-1}\right)/G_{it-1}\right] > 0$; (ii) If $G_{it-1} < 0$ necessarily implies that $G_{it} < 0$ and $\left|G_{it}\right| > \left|G_{it-1}\right|$, since $\textit{Variation}\left(G_{it,t-1}\right) = \left[\left(G_{it} - G_{it-1}\right)/G_{it-1}\right] > 0$.

[39] Mathematical proof with $\textit{Variation}\left(G_{it,t-1}\right) < 0$: (i) If $G_{it-1} > 0$, for $\textit{Variation}\left(G_{it,t-1}\right) = \left[\left(G_{it} - G_{it-1}\right)/G_{it-1}\right] < 0$ to necessarily guarantee a decrease in misallocation, it must be true that $G_{it} > 0$ and $G_{it} < G_{it-1}$, or, expressed differently, it is true that $\left| \textit{Variation}\left(G_{it,t-1}\right) \right| < 1$; (ii) If $G_{it-1} < 0$, for $\textit{Variation}\left(G_{it,t-1}\right) = \left[\left(G_{it} - G_{it-1}\right)/G_{it-1}\right] < 0$ to necessarily guarantee a decrease in misallocation, it must be true that $G_{it} < 0$ and $\left|G_{it}\right| < \left|G_{it-1}\right|$, or, expressed differently, it is true that $\left| \textit{Variation}\left(G_{it,t-1}\right) \right| < 1$.

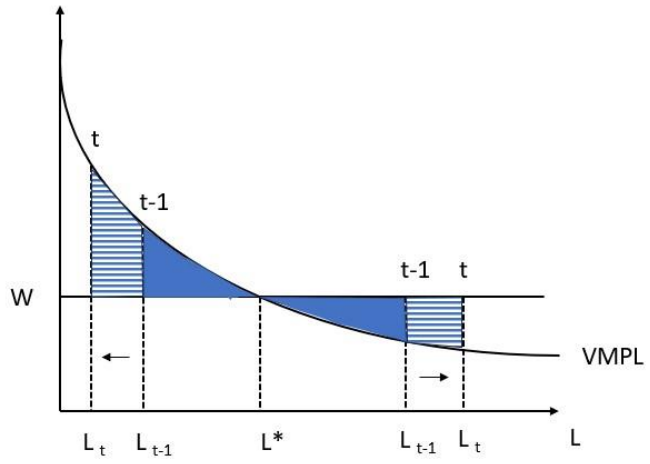
[40] For instance, consider a firm with a gap value of 20 in period *t-1*. In period *t*, the firm may exhibit a gap of -1, indicating a reduction in misallocation, or a gap of -30, signifying an increase in misallocation. In both cases, the growth rate of the gap would be negative. However, in the first scenario, misallocation is reduced, whereas in the second scenario, it is increased. Therefore, relying solely on the information about the negative growth rate of the gap would be uninformative regarding the temporal evolution of input misallocation. In both cases, the absolute value of the growth rate of the gap from period *t-1* to *t* is above 100%.

exclude cases in our empirical analysis where the variation of the gap is both negative and, in absolute value, larger than 100% (as we empirically work with the misallocation measure in percentage). This exclusion is necessary, as we cannot conclusively state that such cases imply a reduction in misallocation.[41]

To sum up, our measure of firm-level misallocation in this chapter for intermediate inputs is the rate of variation of the gap including the information on its sign, conditioned such that when it is negative, we will only consider those with an absolute value below 100%. We will do the same when calculating the misallocation measures for capital and labour inputs in growth rates with the aim of comparing them with those of intermediate inputs. A positive growth rate of the gap increases misallocation, while a negative growth rate, with an absolute value less than 100%, decreases it. The variation in misallocation in the data ranges from -100%, representing the maximum possible reduction, to positive variations indicating increases in misallocation (higher positive gap variations correspond to higher increases in misallocation). Therefore, the identification of a negative sign in the relationship between the percentage change in firms' intermediate input gap and their participation in GVCs would suggest that such participation contributes to improving the allocative efficiency of the input, implying a negative impact on its misallocation.

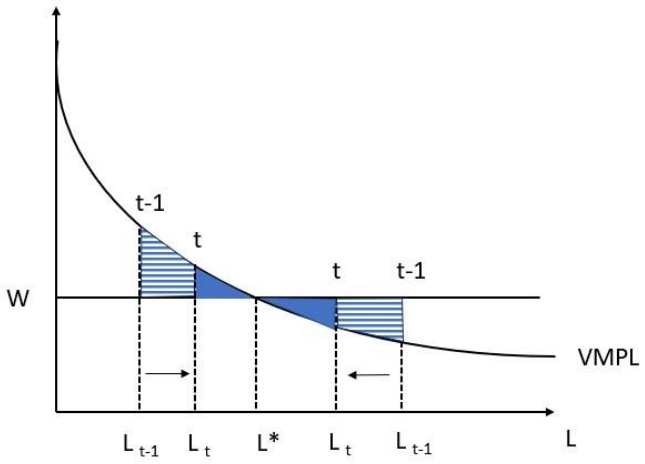
[41] However, for our main focus in this chapter— the gap of intermediates—cases where the absolute value of the variation of the gap exceeds 100% constitute only 0.04% of the total potential observations.

Figure 2.5. Positive variation of the gap.




Source: Own elaboration based on Figure 1 in Petrin and Sivadasan (2013).

Figure 2.6. Negative variation of the gap.




Source: Own elaboration based on Figure 1 in Petrin and Sivadasan (2013).

For comparison with previous work in this area, Table 2.1 presents the mean of the absolute values for both the capital and labour gaps in the first column. Specifically, the

mean value of the absolute gap for capital is 0.84€, and for labour, it is 9.04€.[42] In the second column, the growth rates for both the capital and labour gaps are displayed (9.27% and -0.19%, respectively), along with the growth rate of the intermediates gap (-2.72%). Therefore, the evolution of allocative efficiency of production factors indicates a worse behaviour for the capital input and a more favourable behaviour for the intermediates input, falling in between the behaviour of the labour input. This is in line with Figure 2.2 above.

Table 2.1. Descriptive Statistics – Mean of the gaps.

| | (1)<br>Gaps in levels and in absolute terms | (2)<br>Gaps in growth terms |
|---|---|---|
| $G_{it}^{k}$ | 0.84 | 9.27 |
| $G_{it}^{l}$ | 9.04 | -0.19 |
| $G_{it}^{m}$ | | -2.72 |

As mentioned earlier in Section 2.3, we identify GVC participation using firm-level indicators covering both the intensive margin (FVA and IVA) and the extensive margin (represented by the two-way trader and IVA dummies, which are dichotomised versions of FVA and IVA, respectively). Table 2.2 provides further details on the definition for these variables, while Table 2.3 presents descriptive statistics for them.

[42] We can compare our labour gaps in levels with a previous study that also calculates this gap but for the French case (Fontagné and Santoni, 2019). While we found that the mean gap for Spain is 9.04€ per hour of work, in the case of France they discovered a mean gap of approximately 6€. Unlike us, Fontagné and Santoni (2019) expressed their labour gap in € per worker rather than per hour worked, but we calculated the equivalence in € per hour. It's important to note that we cannot compare the other gaps because literature using this methodology and providing gap values is scarce and has primarily focused on labour.

Table 2.2. Definition of the GVC variables.

| | DEFINITION |
|---|---|
| FVA | Content (share) of intermediate imports embodied in exports. It is a measure of "Backward integration" or "Downstream participation". It identifies the intensive margin of participation in GVCs. In constructing FVA, we derive the value of imported intermediate inputs by applying the percentage of foreign intermediates to the total value of the firm's intermediates. Subsequently, we assume that these imported intermediate inputs are allocated proportionally to the firm's total sales. This proportionality assumption also appears when using databases that provide aggregate measures of FVA at the country or sector-country level, such as UNCTAD-Eora or WIOD. |
| IVA | Content (share) of domestic value added in inputs exported to third economies for further processing and export through value chains. It is a measure of "Forward integration" or "Upstream participation". It identifies the intensive margin of participation in GVCs. In constructing IVA, we initially determine domestic value added as the difference between the firm's production and the value of imported intermediate inputs. Subsequently, we assume that domestic value added is allocated proportionally to the firm's total sales. This proportionality assumption is also present when using databases that provide aggregate measures of IVA at the country or sector-country level, such as UNCTAD-Eora or WIOD. It's essential to note that IVA will only have a positive value for firms declaring in our survey that they produce intermediate inputs, information that otherwise is often missing in typical enterprise surveys. |
| TWO-WAY TRADER | Dummy variable that takes the value 1 if the firm imports intermediates and exports (either intermediates or final goods). It is the dummy variable of FVA. It identifies the extensive margin of participation in GVCs. |
| IVA DUMMY | Dummy variable that takes the value 1 if the firm exports intermediate inputs that incorporate domestic value added. It's important to note that, since there is always a positive value of incorporated domestic value added, this dummy variable effectively identifies firms that export intermediates. It is the dummy variable of IVA. It identifies the extensive margin of participation in GVCs. |

Note: (i) Variables have been constructed using data from the ESEE dataset. (ii) For the construction of these variables, we stick to the period 2006-2017, as only from 2006 onwards has the survey included questions on imports of intermediate inputs, a crucial variable for our analysis.

Table 2.3. Descriptive statistics – GVC indicators.

| | Percentage of firms | Mean (intensive margin) | Mean (intensive margin) for participants |
|---|---|---|---|
| FVA/Two-way trader | 40% | 0.23 | 0.50 |
| IVA | 36% | 0.24 | 0.69 |

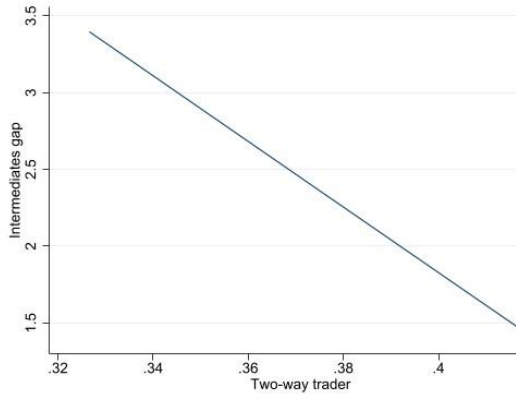
Note: (i) Recall that two-way trader is the dummy of having FVA. (ii) Data for the two-way trader and IVA variables is available starting from 2006.

Table 2.3 shows that 40% of firms are two-way traders, meaning that they import intermediates and export (either intermediates or final goods). This is the most widely used measure in the literature to identify participation in GVCs at the firm-level (although, unlike us, it is often not possible to distinguish whether the firm imports intermediates). Furthermore, as far as IVA is concerned, 36% of firms participate in GVCs. This percentage is lower than the percentage of firms having a positive FVA,

which is reasonable given the context of a developed country. Developed countries tend to participate more in GVCs through backward integration, which is in line with our results for Spain. Moreover, the average value of FVA is 0.23 (23%) and that of IVA is 0.24 (24%). In other words, the share of imported intermediate inputs embodied in exports is 23% and the domestic value added contained in intermediate inputs sent to third economies for further processing and export through value chains is 24%. If we condition the value of FVA and IVA on firms participating in GVCs, these values are 0.5 (50%) and 0.69 (69%), respectively.

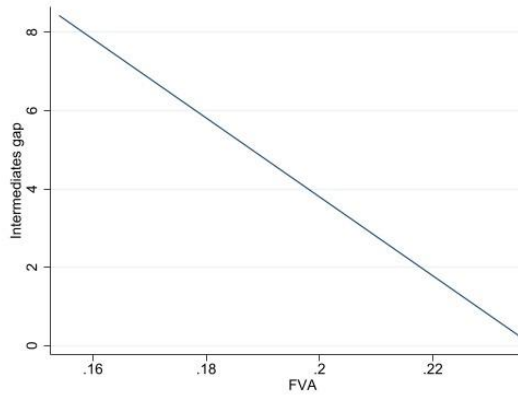
The last part of our descriptive analysis in this chapter aims to present graphical evidence for our main working hypothesis, i.e., that firms' involvement in GVCs contributes to reducing the misallocation of intermediate inputs. To achieve this, we will illustrate in several graphs the fitted lines of scatter plots depicting the relationship between the yearly mean of the intermediate inputs gap measure and the yearly mean of the different GVC variables.[43]

Figure 2.7. Intermediates misallocation and two-way trader.




Source: ESEE.

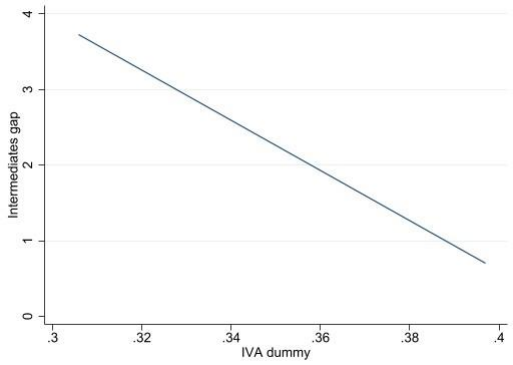
Figure 2.8. Intermediates misallocation and FVA




Source: ESEE.

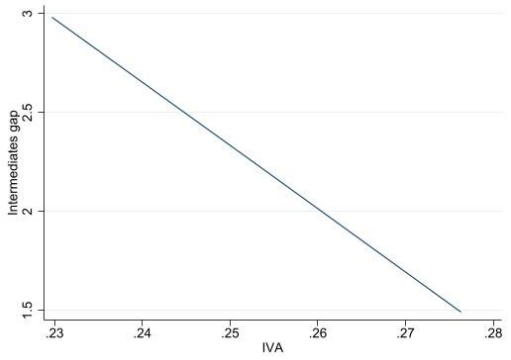
[43] Means are calculated taking into account both the representativeness of SMEs and large firms in the ESEE and the weight of each industry in total manufacturing GDP.

Figure 2.9. Intermediates misallocation and IVA dummy.




Source: ESEE.

Figure 2.10. Intermediates misallocation and IVA.




Source: ESEE.

Figures 2.7-2.10 show the relationships between the intermediates gap measure and the different measures of GVCs. Figure 2.7 includes the dummy of two-way trader, which takes the value 1 if the firm imports intermediate inputs and exports (either intermediates or final goods). Figure 2.8 plots the variable FVA, identifying the downstream participation (or backward integration). Or in other words, the content of intermediate imports embodied in exports. Figures 2.9 and 2.10 include the IVA measure in their dummy and continuous form, respectively, which identify the upstream participation or forward integration. Or what is the same, domestic value added contained in intermediate inputs exported to third economies for further processing and export through value chains. Hence, using all different measures of GVCs, we see that all these figures show a negative relationship between GVC participation and the intermediates gap measure. This provides the first evidence of the role that GVC engagement may have in alleviating intermediates misallocation. Moreover, this is consistent with the trend in GVC participation in Spain (Figure 2.3) and the evolution of intermediates misallocation (Figure 2.2). As GVC participation has been on the rise, intermediates misallocation has been decreasing, which aligns with the negative relationship depicted in Figures 2.7-2.10.

## 2.5. Estimation Results

In what follows, we are interested in whether the intermediates gap measure responds to firm's GVC participation. In other words, we want to evaluate how GVC engagement affects intermediates misallocation. In order to do so, we start by estimating a linear regression, and then we exploit the panel structure of the data to implement what is called a "two-way fixed effects" (TWFE) estimator. The latter consists of including both firm fixed effects and time fixed effects in ordinary least squares estimation. This helps to deal with the likely presence of unobserved heterogeneity, i.e. firms' individual effects, and removes potential changes in the economic environment that have the same effect on all firms (Wooldridge, 2021).

The baseline estimated equation is defined as:

$$G_{i,t}^{m} = \beta_0 + \beta_1 GVC_{i,t} + \delta_s + \delta_t + \delta_{s,t} + \delta_i + \epsilon_{i,t} \qquad (2.4)$$

where $G_{i,t}^{m}$ is the growth rate of the intermediates gap in percentage, $GVC_{i,t}$ is the variable identifying GVC participation, $\delta_s + \delta_t + \delta_{s,t}$ are industry, year and industry-year fixed effects, and $\delta_i$ are firm fixed effects included when estimating with TWFE.

Table 2.4. Intermediates misallocation – Linear Regression (OLS).

| | Growth rate of the intermediates gap in percentage $G_{i,t}^{m}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Two-way trader | -3.025*** | | | |
| | (0.929) | | | |
| FVA | | -6.893*** | | |
| | | (1.474) | | |
| IVA dummy | | | -0.329 | |
| | | | (0.590) | |
| IVA | | | | -0.401 |
| | | | | (0.760) |
| Constant | -2.216 | -2.216 | -3.106 | -3.106 |
| | (1.955) | (1.955) | (2.178) | (2.178) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Industry-Year FE | YES | YES | YES | YES |

| | | | | |
|---|---|---|---|---|
| Firm FE | NO | NO | NO | NO |
| Observations | 8,517 | 8,511 | 9,235 | 9,235 |

Note: (i) Robust standard errors clustered by firm in parentheses (ii)*** p<0.01

Table 2.5. Intermediates misallocation – TWFE.

| | Growth rate of the intermediates gap in percentage $G_{i,t}^{m}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Two-way trader | -2.904** | | | |
| | (1.459) | | | |
| FVA | | -6.725*** | | |
| | | (2.141) | | |
| IVA dummy | | | 1.270 | |
| | | | (1.033) | |
| IVA | | | | 1.429 |
| | | | | (1.336) |
| Constant | 1.072*** | 1.397*** | -2.163*** | 2.143*** |
| | (0.202) | (0.232) | (0.091) | (0.086) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Industry-Year FE | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES |
| Observations | 8,517 | 8,511 | 9,235 | 9,235 |

Note: (i) Robust standard errors clustered by firm in parentheses (ii)*** p<0.01, ** p<0.05

Tables 2.4 and 2.5 present the results. GVC participation is identified using the two-way trader dummy (indicating the extensive margin of GVC participation), FVA (indicating the intensive margin of GVC participation), and IVA (both as a dummy and in its continuous form, thereby identifying both the extensive and intensive margins of GVC participation). The results show that participating in GVCs alleviates intermediates misallocation. However, we can see that the coefficient is significant for two-way trader and FVA. These results suggest that what matters most for reducing the misallocation of intermediates is participation in GVCs as an importer of intermediate inputs incorporated in the production of other goods that the firm exports.

However, the TWFE estimator has limitations, primarily in interpreting results as causal effects. It assumes treatment occurs simultaneously for all individuals, which

doesn't align with our case as not all firms engage in GVCs in the same year. Hence, relying just on the TWFE might be insufficient, as it overlooks the heterogeneity of treatment effects, leading to the "bad/forbidden comparison" problem.[44] Therefore, to address this, we exploit the variation in treatment times, acknowledging that firms may be treated at different times. To accomplish this, we adopt Callaway and Sant'Anna's (2021) setup and implement a Difference-in-Differences (DiD) estimator with staggered adoption.

We can only apply this methodology to discrete binary treatments. Thus, we employ the dummy variables representing being a two-way trader and having a positive IVA.[45] Hence, in this chapter, beyond descriptives, OLS, and TWFE estimators, we advance towards establishing causality by implementing this staggered DiD.

Callaway and Sant'Anna's (2021) proposal for staggered DiD extends the original concept of combining propensity score matching with DiD to estimate causal treatment effects. In the standard or more traditional case of DiD analysis, a control group of firm observations with the same probability of receiving the treatment (in our case, participating in GVCs) is obtained through the matching process. Subsequently, a DiD analysis is performed using the group of treated firms and their matched controls. This approach ensures that if treated firms have the same probability of receiving the treatment (conditional on a set of pre-treatment variables) as untreated firms, any difference between the two groups after the treatment can be attributed to the treatment itself.

[44] The TWFE regressions not only compare treated and not-treated units but also involve "forbidden" or "bad" comparisons among units that are already-treated, and this may lead to poor estimates of causal effect parameters. For a more comprehensive discussion of the limitations of the TWFE estimator, please refer to Roth et al. (2023).

[45] Note that the dummy variable for FVA is the two-way trader dummy.

The extension performed by the staggered DiD methodology consists of performing the matching for each generation (cohort) of treated, as they receive treatment at different times, and to allow for dynamics of the causal effects of treatment as the time since treatment increases. This methodology also allows parallel trends to be tested prior to treatment. To implement this methodology with our data and our treatment variables, we use the same specification as the one in equation (2.4), and we further consider a set of variables to test the conditional parallel trends assumption between the treatment and control groups. This set of variables contains: Total Factor Productivity (TFP), the number of workers, the expenditure in R&D, the share of skilled workers and our gap measure of intermediates misallocation.[46] All these variables are used in their pre-treatment values.

For the implementation of the staggered DiD, we define treated firms as those that start participating in GVCs during our time window and track all subsequent periods during which they systematically continue this activity after initiation.[47] Control firms, on the other hand, are those that never participate in GVCs. For the case of two-way trader, we consider 8,517 observations, corresponding to 1,377 firms, of which 360 started participating in GVCs for the first time at some point between 2006 and 2017, while 1,017 firms never engaged in GVCs during this period. For the case of IVA, we consider 9,235 observations, corresponding to 1,477 firms, of which 243 started participating in GVCs for the first time at some point in this period, while 1,234 firms never participated in GVCs.

Table 2.6 shows the average treatment effect on the treated (ATT) for the two dichotomised measures of GVC participation. Only the two-way trader dummy exhibits

[46] These variables are used in growth terms, as the gap of intermediates is also expressed in this way.
[47] These treated firms include those that always participate in GVCs after initiation, as well as those that participate for several years but cease to do so at a future point in time. For the latter, information is only used up to the year in which they stop participating.

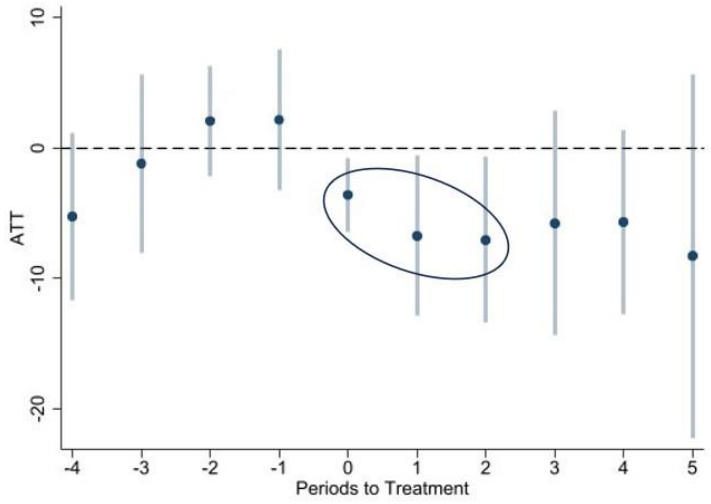
statistical significance. This implies that when a firm engages in GVCs as a two-way trader, equivalent to having a positive FVA, it reduces the intermediates gap by an average of 10.233 percentage points. Figure 2.11 depicts this effect over time, indicating that the impact of being a two-way trader diminishes the intermediates gap for three years from the adoption of treatment, after which the effect disappears. However, having a positive IVA shows no significant effect on the intermediates gap, neither on average nor over time (see Figure 2.12). These findings are consistent with those reported in Table 2.5.

Table 2.6. Intermediates misallocation – Staggered DiD (ATT).

| | Growth rate of the intermediates gap in percentage $G_{i,t}^{m}$ | |
|---|---|---|
| Two-way trader | -10.233** | |
| | (4.167) | |
| IVA | | -0.306 |
| | | (0.867) |
| Observations | 8,517 | 9,235 |
| Pretrend test | 0.539 | 0.505 |
| | (2.032) | (0.880) |

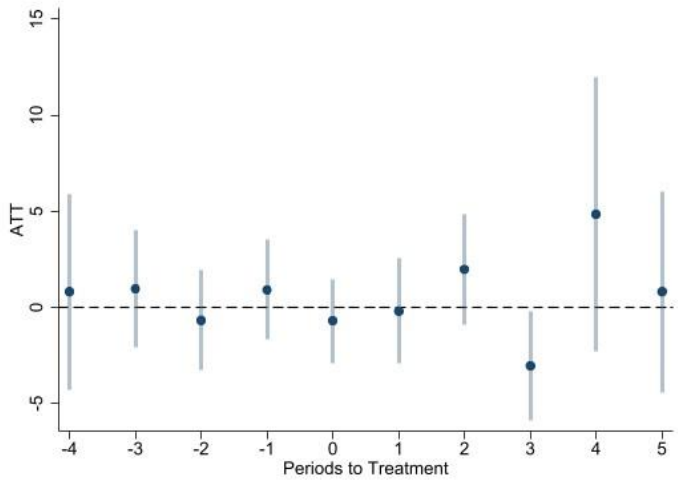
Notes: (i) Estimation method: Sant'Anna and Zhao (2020) doubly robust DiD estimator based on stabilised inverse probability weighting and ordinary least squares (ii) Bootstrapped standard errors (iii)** p<0.05 (iv) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, as we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure 2.11. ATT – The effect of two-way trader on intermediates gap.




Note: The period t = 0 corresponds to the first year the firm is a two-way trader. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Figure 2.12. ATT – The effect of IVA on intermediates gap.




Note: The period t = 0 corresponds to the first year the firm has IVA. The bars are 90% confidence intervals for each yearly estimated effect (dot).

To further reinforce the causality argument and take advantage of the non-binary nature of the intensive margin measure FVA, we can consider a scenario in which a shock impacts the functioning of GVCs. In this scenario, firms that were more involved in GVCs prior to the shock, as indicated by their higher FVA values, are expected to be more affected by the shock. Consequently, this shock is anticipated to have varying implications for the misallocation of intermediates among firms with different levels of exposure to GVC participation before the shock.

For GVCs we can think about digitalisation and ICT as a positive shock to their functioning. The use of information and communication technologies (ICT) is one of the factors behind the increase in trade activities (Añón Higón and Bonvin, 2022; Yushkova, 2014), and in particular they are associated to an increase in GVC participation. In fact, Baldwin (2016) already claimed that the ICT revolution is the technology breakthrough behind the international dispersion of activities within GVCs. Hence, the ICT use can be seen as a positive shock to GVCs, or in other words, as a smoothing factor in the operation of GVCs.

Particularly, broadband applications are one of the communication technologies already allowing for more efficient communication within GVCs (De Backer and Flaig, 2017). The broadband service can be provided through multiple technologies. Traditionally, it has been provided over the xDSL technology family (usually over copper cable), but in general, its speed is not enough. That is why the European Digital Agenda considers fibre-based technology as key to meeting connectivity goals (Telefónica, 2021). According to the CNMC (the Spanish National Markets and Competition Commission) in 2010 more than 99% of the service lines in Spain used the xDSL technology. However, that year the first fibre optics deployments were carried out, and in 2013 fibre optics became the fastest-growing technology in Spain. In fact, from 2013 to 2018 the fibre optics coverage had an average increase of 12.98% per year (Jesús-Azabal et al., 2021).

Hence, the deployment and explosion of the fibre optics can be understood as a positive shock to GVCs. This way, firms that were more exposed to GVCs before the expansion of the fibre optics should benefit more from this positive shock. Thus, these firms with a higher engagement in GVCs before the shock should decrease more the misallocation of intermediates in comparison to those that were less exposed to the positive shock.

To assess the relationship of the fibre optics expansion and the misallocation of intermediates we rely on the following panel regression framework that consists on a DiD with continuous treatment intensity approach following Alpysbayeva and Vanormelingen (2022):

$$G_{i,t}^{m} = \beta_1 FVA_i + \beta_2 FIBRE\ OPTICS_t + \alpha\ FVA_i \times FIBRE\ OPTICS_t + \delta_s + \delta_t + \delta_{s,t} + \delta_i + \epsilon_{i,t} \quad (2.5)$$

where $FVA_i$ is the value of FVA in 2010 (the year of the deployment of the fibre optics in Spain)[48] for firm *i* and $FIBRE\ OPTICS_t$ is a dummy indicating the period where the fibre optics was the fastest growing technology (2013-2017). $\delta_s + \delta_t + \delta_{s,t} + \delta_i$ are sector, year, sector-year and firm fixed effects and $\epsilon_{i,t}$ is an iid error term. We will control first just for sector, year and sector-year fixed effects, and secondly, we will control as well for firm fixed effects.[49] $\alpha$ is the coefficient of interest, which indicates the impact of the fibre optics expansion depending on the pre-fibre optics FVA. A negative $\alpha$ means that misallocation of intermediates has decreased more after the expansion of the fibre optics for firms with an ex-ante higher FVA. Or in other words, post-expansion allocative efficiency of higher participants in GVCs has increased relative to lower participants in GVCs. Table 2.7 shows these results.

Table 2.7. Intermediates misallocation – Shock to the functioning of GVCs (fibre optics).

| | Growth rate of the intermediates gap in percentage $G_{i,t}^m$ | |
|---|---|---|
| | (1) OLS | (2) TWFE |
| $FVA_{2010}$ × FIBRE $OPTICS_{2013}$ | -5.152** | -5.689** |
| | (2.397) | (2.438) |
| Constant | -3.952** | 0.149 |
| | (1.543) | (0.217) |
| Observations | 16,075 | 16,030 |

Note: (i) Robust standard errors clustered by firm in parentheses (ii)*** p<0.01, ** p<0.05 (iii) All regressions include $FVA_i$, and $FIBRE\ OPTICS_t$ (iv) Column (1) includes industry, year and industry-year fixed effects, while column (2) includes industry, year, industry-year and firm fixed effects.

Under both OLS and TWFE estimators, we confirm that after the fibre optics expansion, firms with a higher FVA reduced more their intermediates misallocation.

[48] We take the value of 2010, the year of the deployment of the fibre optics, to have cleaner results. Choosing a year after the deployment may be biased due to the potential effect the fibre optics has.

[49] Please note that $FIBRE\ OPTICS_t$ will be absorbed by year-fixed effects and $FVA_i$ will be absorbed by firm-fixed effects.

Hence, firms that had higher engagement in GVCs could benefit more from the positive shock to the functioning of GVCs, and this is translated into a greater reduction of intermediates misallocation. This means that firms that were more involved in GVCs benefited more with the expansion of the fibre optics, since it allowed them to have a more efficient communication within GVCs.

## 2.6. Robustness

To further validate the main results, we will conduct a series of robustness checks. Given that the earlier results suggest that being a two-way trader is the type of GVC participation that reduces intermediates misallocation, our focus in this section will be on this measure.

Firstly, we continue implementing the staggered DiD method with the same specification as before, but in this case using a balanced panel.[50] This allows us to rule out compositional confounds around the first treatment year. Nevertheless, it might come with some drawbacks, such as the potential exclusion of young firms (Alfaro-Ureña et al., 2022).

Table 2.8 shows the results for the staggered DiD using a balanced panel for two-way trader. The negative effect of being a two-way trader on the intermediates gap confirms the impact of this type of GVC participation on intermediates misallocation. Moreover, Figure 2.13 displays its evolution, where it can be seen that the effect is present during the first and second year after starting its participation in GVCs (with the effect also approaching significance in the year of treatment initiation).

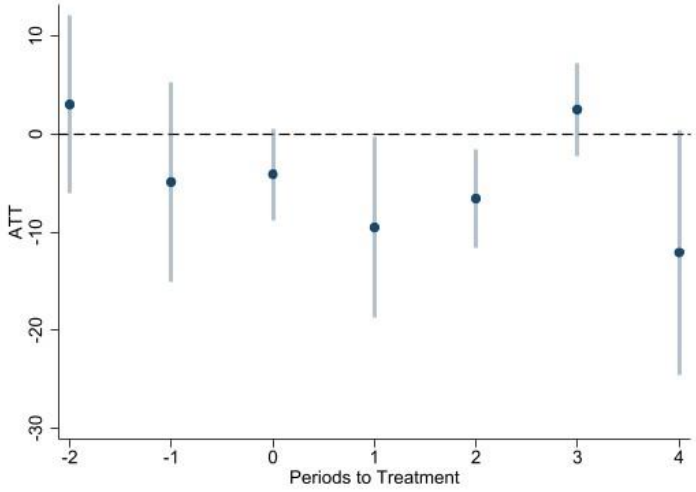
[50] We take firms that were present in the data 3 years prior to the treatment and 4 years after the treatment. As shown in Figure 2.11, this time span is enough to see the results.

Table 2.8. Intermediates misallocation – Staggered DiD with balanced panel.

| | Growth rate of the intermediates gap in percentage $G_{i,t}^{m}$ |
|---|---|
| Two-way trader | -5.892** |
| | (2.396) |
| Observations | 5,845 |
| Pretrend test | -0.945 |
| | (4.170) |

Notes: (i) Estimation method: Sant'Anna and Zhao (2020) doubly robust DiD estimator based on stabilised inverse probability weighting and ordinary least squares (ii) Bootstrapped standard errors (iii) ** p<0.05 (iv) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, as we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure 2.13. ATT – The effect of two-way trader on intermediates gap (balanced panel).




Note: The period t = 0 corresponds to the first year the firm is a two-way trader. The bars are 90% confidence intervals for each yearly estimated effect (dot).

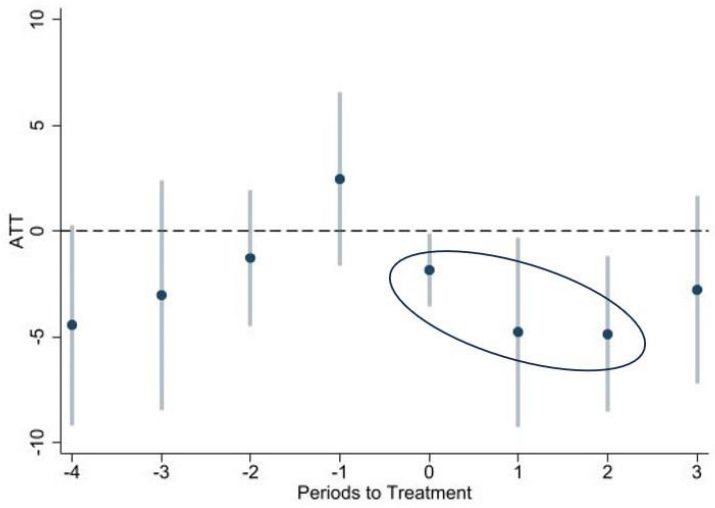
Secondly, as discussed in Section 2.3, we will calculate our intermediates gap measure using a Translog production function. Tables 2.9 and 2.10, along with Figure 2.14, present the primary results obtained in the previous section but utilising the Translog production function to calculate the gap measure.

Table 2.9. Intermediates misallocation (Translog production function) –Staggered DiD (ATT).

| | Growth rate of the intermediates gap in percentage $G_{i,t}^{m}$ |
|---|---|
| Two-way trader | -7.672*** |
| | (2.922) |
| Observations | 7,735 |
| Pretrend test | -1.576 |
| | (1.551) |

Note: (i) Estimation method: Sant'Anna and Zhao (2020) doubly robust DiD estimator based on stabilised inverse probability weighting and ordinary least squares (ii) Bootstrapped standard errors (iii)*** p<0.01 (iv) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, as we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure 2.14. ATT – The effect of two-way trader on the growth rate of the intermediates gap in percentage (Translog production function).




Note: The period t = 0 corresponds to the first year the firm is a two-way trader. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Table 2.10. Intermediates misallocation (Translog production function) – Shock to the functioning of GVCs (fibre optics).

| | Growth rate of the intermediates gap in percentage $G_{i,t}^{m}$ | |
|---|---|---|
| | (1) OLS | (2) TWFE |
| $FVA_{2010}$ × FIBRE $OPTICS_{2013}$ | -3.277** | -3.481** |
| | (1.353) | (1.470) |
| Constant | -3.953** | -1.331*** |
| | (1.543) | (0.140) |
| Observations | 14,758 | 14,703 |

Note: (i) Robust standard errors clustered by firm in parentheses (ii) *** p<0.01, ** p<0.05 (iii) All regressions include $FVA_i$, and $FIBRE\ OPTICS_t$ (iv) Column (1) includes industry, year and industry-year fixed effects, while column (2) includes industry, year, industry-year and firm fixed effects.

Table 2.9 shows the results using the staggered DiD, where we confirm the results we got with the Cobb-Douglas production function. Likewise, Figure 2.14 shows that firms experience a reduction in the intermediates gap for three years.[51] Finally, Table 2.10 shows that the results of the DiD with continuous treatment intensity approach, exploiting the expansion of the fibre optics as an exogenous shock to the functioning of GVCs, also hold. In other words, the results remain robust even when using the Translog production function to calculate the intermediates gap measure.

Finally, since two-way trader seems to be the most important indicator of GVC participation when dealing with intermediates misallocation, it is convenient to disentangle its composition. Being a two-way trader means that the firm imports intermediates and exports. Thus, which is the effect on intermediates misallocation of importing intermediates and exporting, separately?

[51] After the third year, the effect becomes insignificant, but from the fourth year it is not shown because the coefficient of the fourth year is much lower than the rest of the years (although insignificant). Thus, when plotting the results, it becomes challenging to appreciate the coefficients of the other years. However, we include the dynamic effects, including this fourth year, in Figure A2.1 in Appendix 2.

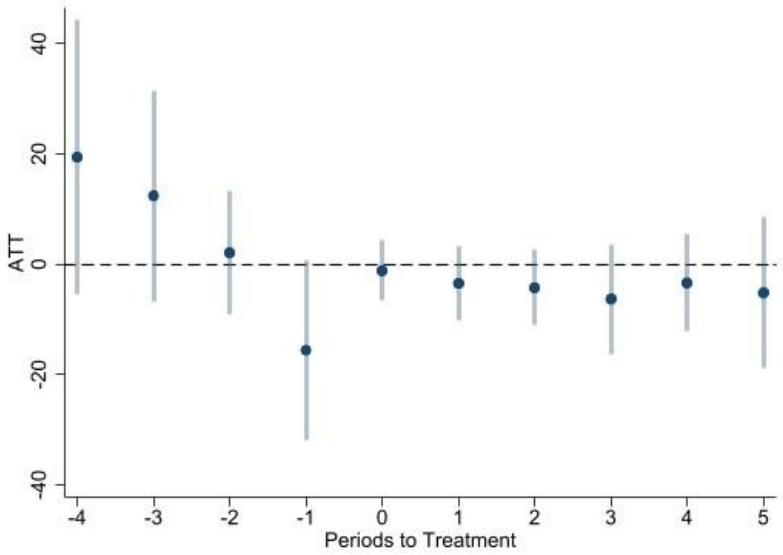
Table 2.11 shows the effect of only importing intermediates, only exporting and being a two-way trader, while Figures 2.15 and 2.16 display the effect over the years of only importing intermediates and only exporting, respectively. Neither only importing intermediates nor only exporting have a significant effect on the intermediates gap. However, it is when both activities are combined, i.e. when firms engage in GVCs as two-way traders, that this effect on the misallocation of intermediates becomes negative and significant. This seems to imply that the confluence of both activities (a better indicator of participation in GVCs than the isolated ones) is more relevant for reducing the misallocation of this factor of production. This underscores the significance of possessing a thorough understanding of international markets in order to reduce the intermediates gap. Engaging in GVCs allows firms to acquire comprehensive understanding of international markets by acquiring knowledge about both supplier and buyer markets. This highlights the complementarities between importing intermediates and exporting (Kasahara and Lapham, 2013; Máñez et al., 2020; Máñez Castillejo et al., 2020). On the one hand, exporters, equipped with knowledge and experience in international markets, may find it easier to integrate foreign inputs into their production processes. Moreover, they might experience competitive pressure from other traders who incorporate more suitable inputs. On the other hand, importers of intermediate inputs can benefit from the diffusion of new technologies and knowledge embodied in these imported inputs, thus facilitating their exports. Consequently, the performance of one activity may amplify the benefits expected from the other. These activities involve not only the flow of goods and materials between firms in different countries, but also intangibles such as information, technology, or management knowledge (Timmer, 2017; Antràs, 2020).

Table 2.11. Intermediates misallocation – Staggered DiD disentangling two-way trader (ATT).

| | Growth rate of the intermediates gap in percentage $G_{i,t}^{m}$ | | |
|---|---|---|---|
| Only Import intermediates | -2.594<br>(1.882) | | |
| Only Export | | 0.773<br>(2.046) | |
| Two-way trader | | | -10.233**<br>(4.167) |
| Observations | 7,565 | 4,565 | 8,517 |
| Pretrend test | 4.545<br>(5.741) | -2.751<br>(5.007) | 0.539<br>(2.032) |

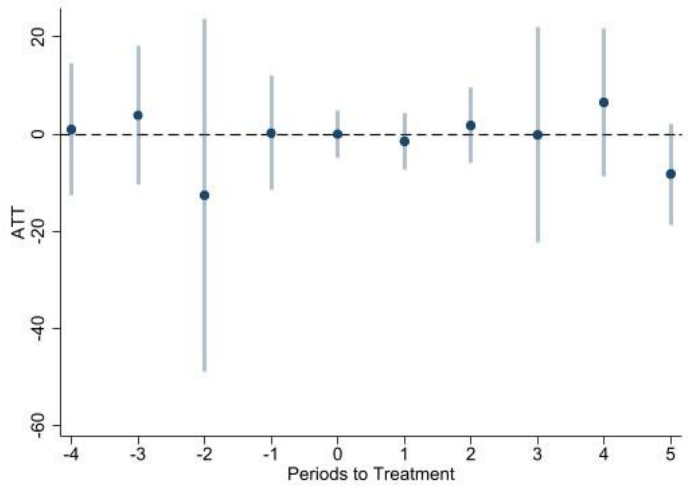
Notes: (i) Estimation method: Sant'Anna and Zhao (2020) doubly robust DiD estimator based on stabilised inverse probability weighting and ordinary least squares (ii) Bootstrapped standard errors (iii)** p<0.05 (iv) Importing intermediates means that the firm only does this activity, but does not export. In the same way, exporting means that the firm only does this, but does not import intermediates. (v) The result of two-way trader is the same as in Table 2.6, but we repeat it in here for convenience. (vi) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, as we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure 2.15. ATT – The effect of only importing intermediates on intermediates gap.




Note: The period t = 0 corresponds to the first year the firm imports intermediates. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Figure 2.16. ATT – The effect of only exporting on intermediates gap.




Note: The period t = 0 corresponds to the first year the firm exports. The bars are 90% confidence intervals for each yearly estimated effect (dot).

## 2.7. Conclusion

This chapter analyses firms' misallocation of intermediate inputs and its relation to Global Value Chains (GVCs). In order to do so, this chapter applies Petrin and Sivadasan (2013)'s methodology to study misallocation from a firm-level point of view.

Using a firm-level panel dataset for manufacturing firms provided by the Spanish Survey on Business Strategies (ESEE) for the period 1991-2017, we contribute to the literature on the study of misallocation adding several novelties. First, in this chapter we focus on the study of the misallocation of intermediate inputs, while previous papers focused on capital or labour. Second, we are able to unravel a factor that helps reduce intermediates misallocation: the engagement in GVCs. Both contributions are significant as there is not only a scarcity of studies on the misallocation of intermediate inputs but also a lack of research on its underlying causes. Third, and in contrast to most previous work on production factors misallocation, we conducted the analysis from a firm-level perspective, while other papers had a more aggregated viewpoint. Fourth, our database

allows us to use firm-level output and input deflators, while other papers use industry deflators, which may introduce a bias in the estimates of intermediate input elasticities in the production function. Finally, our chapter combines descriptive and graphical tools, OLS and TWFE estimation methods, and, for the binary indicators of GVC participation, deepens causality with recent staggered DiD estimation methods (Callaway and Sant'Anna, 2021) and DiD with continuous treatment intensity approach.

Through the regression analysis presented in this chapter, and as a major contribution, we find that participation in GVCs helps alleviate misallocation of intermediates. This finding is further substantiated by employing the more demanding staggered DiD methodology for causal inference and a DiD approach with a continuous treatment intensity. The latter exploits the emergence and expansion of fibre-optic-based ICT technology that facilitates the operation of GVCs. Indeed, following the introduction of fibre optics in Spain, the enhancement in the allocation of intermediates is particularly noticeable among firms that were more deeply involved in GVCs before this technological shock. This suggests that the increased ease and efficiency in operations within the supply chains, brought about by the arrival of this technological change, had a substantial impact on these firms. Our findings are further strengthened by robustness checks in the chapter, such as the use of a Translog instead of a Cobb-Douglas production function.

The results suggest that firms participating in GVCs can alleviate sourcing constraints by gaining greater access to intermediate inputs through international sourcing, enabling them to navigate and mitigate frictions in intermediate input markets more effectively than firms exclusively sourcing domestically. Additionally, engaging in GVCs may allow firms to acquire knowledge about both supplier and buyer international markets and integrate this knowledge with their understanding of the domestic market.

Since the misallocation of factors of production affects not only the aggregate output of the economy, but also TFP growth, this chapter can assist policy makers in uncovering the reasons behind it. In particular, trade policies should consider that GVC engagement contributes to the reduction of misallocation. Therefore, restrictions on the functioning of GVCs should be taken with caution, as they may have undesirable effects on allocative efficiency and, consequently, on TFP and output growth. In other words, the implications of GVC engagement on misallocation should be carefully considered when designing or modifying trade policies. This is of particular importance in light of the potential rise in protectionist policies that could hinder the functioning of GVCs.

Particularly for Spain, unravelling that GVC participation is behind the decrease in intermediates misallocation can contribute to understanding the improved evolution of Spanish TFP experienced after the 2008 crisis. Policy makers should always be interested in understanding how to enhance TFP due to its implications for economic growth. However, it is of special interest for Spain because productivity is one of the structural problems of the Spanish economy (Fundación BBVA and Ivie, 2019). Hence, this study contributes to future policies by disentangling one of the factors behind the decrease in misallocation, which can be used to boost TFP.

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# APPENDIX 2

Table A2.1. Definition of variables utilised in estimating the production function and those involved in measuring misallocation.

| VARIABLE | DEFINITION |
|---|---|
| OUTPUT ($q_{it}$) | Value (in euros) of the production of goods and services, deflated by a firm-specific price index of output. The price index is a Paasche-type one constructed starting from the percentage price changes on output reported by the firm. |
| LABOUR ($l_{it}$) | Total number of hours worked. |
| CAPITAL ($k_{it}$) | Capital at current replacement values $K_{it}$ (in euros) is computed recursively from an initial estimate and data on current investments in equipment goods $I_{it}$ (excluding buildings, land, and financial assets). The value of the past stock of capital is updated by means of the price index of investment $P_{I_t}$ as $K_{it} = (1-\delta)\frac{P_{I_t}}{P_{I_{t-1}}}K_{it} + I_{it}$, where $\delta$ is an industry-specific estimate of the rate of depreciation. Capital in real terms is obtained by deflating capital at current replacement values by the price index of investment as $\widetilde{K}_{it} = \frac{K_{it}}{P_{I_t}}$. The price index of investment is obtained as the equipment goods component of the index of industry prices published by the Spanish National Institute of Statistics. This method has been already employed in other papers with the ESEE (see, for instance, Doraszelsky and Jaumandreu, 2018, Martín-Marcos and Moreno-Martín, 1991, and Martín-Marcos and Suárez, 1997). |
| INTERMEDIATE INPUTS ($m_{it}$) | Value (in euros) of intermediate consumption deflated by a firm-specific price index of intermediate inputs. The price index is a Paasche-type one constructed starting from the percentage price changes on intermediates consumption reported by the firm. |
| WAGE PER UNIT OF LABOUR ($w_{it}$) | Wage per hour, computed as total labour cost divided by total hours worked. |
| COST PER UNIT OF CAPITAL ($r_{it}$) | Cost per unit of capital calculated as the sum of the firm-specific interest rate in long-term debt and an industry-specific estimate of the rate of depreciation. This total is then reduced by the rate of inflation, determined using the price index of investment, which is obtained from the equipment goods component of the index of industry prices published by the Spanish National Institute of Statistics. |
| PRICE PER UNIT OF INTERMEDIATE INPUT ($p_{it}^{m}$) | Price per unit of intermediate input expressed as the annual variation in the price of intermediate inputs. |

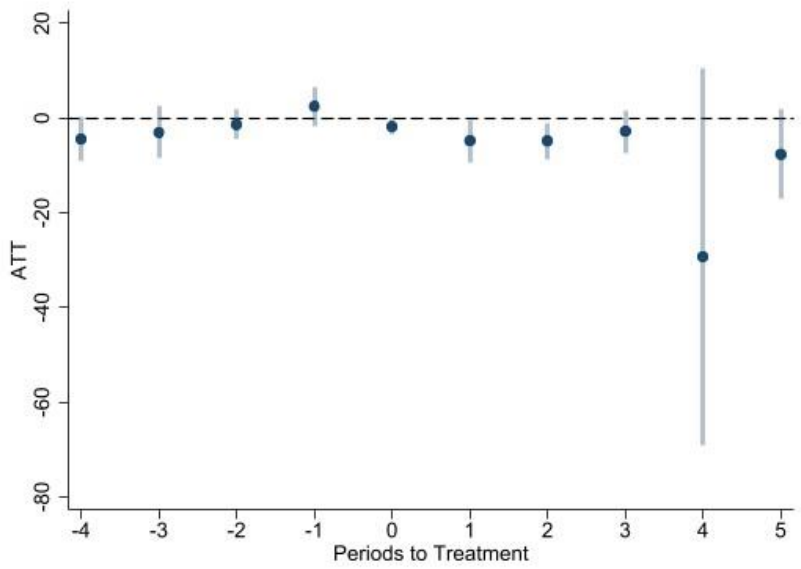
Note: All variables come from the ESEE and are available for the whole time span (1991-2017).

Table A2.2. Input coefficients by sector.

| | Input coefficients | | |
|---|---|---|---|
| | $\beta_k$ | $\beta_l$ | $\beta_m$ |
| Meat products | 0.132 | 0.11 | 0.565 |
| Food and tobacco | 0.127 | 0.144 | 0.636 |
| Beverage | 0.072 | 0.179 | 0.721 |
| Textiles and clothing | 0.107 | 0.33 | 0.412 |
| Leather, fur and footwear | 0.036 | 0.268 | 0.416 |
| Timber | 0.085 | 0.235 | 0.566 |
| Paper | 0.122 | 0.234 | 0.369 |
| Printing (before Printing and Edition) | 0.072 | 0.307 | 0.512 |
| Chemicals and pharmaceuticals | 0.135 | 0.117 | 0.685 |
| Plastic and rubber products | 0.148 | 0.249 | 0.475 |
| Nonmetal mineral products | 0.112 | 0.235 | 0.53 |
| Basic metal products | 0.166 | 0.067 | 0.441 |
| Fabricated metal products | 0.074 | 0.27 | 0.519 |
| Machinery and equipment | 0.126 | 0.171 | 0.504 |
| Computer products, electronics and optical | 0.084 | 0.259 | 0.427 |

| | | | |
|---|---|---|---|
| Electric materials and accessories | 0.118 | 0.283 | 0.466 |
| Vehicles and accessories | 0.077 | 0.134 | 0.527 |
| Other transport equipment | 0.106 | 0.148 | 0.661 |
| Furniture | 0.054 | 0.29 | 0.353 |
| Other manufacturing | 0.097 | 0.275 | 0.529 |
| Overall | 0.105 | 0.22 | 0.518 |

Figure A2.1. The effect of two-way trader on intermediates gap (translog production function).




Note: The period t = 0 corresponds to the first year the firm is a two-way trader. The bars are 90% confidence intervals for each yearly estimated effect (dot).

# Chapter 3. How do firms in Sub-Saharan Africa benefit from Global Value Chains?

## 3.1. Introduction

Nowadays, one cannot talk about international trade without talking about Global Value Chains (GVCs). Their development has been remarkable. In almost all regions of the world, participation in GVCs has been increasing (Del Prete et al., 2017; De Melo and Twum, 2021). This has also been the case for African countries, which have been particularly dynamic in recent years, with trade growth outpacing that of most economies.[52] Still, Sub-Saharan Africa is the world's least integrated region in GVCs.

GVCs represent an opportunity for developing countries to enter global markets (Stamm, 2004; Kowalski et al., 2015). They can join them and save decades of investment in forming their own supply chains (Baldwin, 2013). But, what are the factors that determine firms' participation in GVCs? And, can firms benefit from this participation? Answering these questions leads to the twofold objective of this work: to identify the factors, especially those in the business environment, that influence firms' participation in GVCs, and to analyse the effects of participation on some relevant measures of firm performance. In particular, this chapter will focus on their impact on innovation incentives for product upgrading and production efficiency, as well as on firms' productivity, wages and employment. To achieve these goals, we use rich firm-level data from the World Bank Enterprise Survey (WBES, hereafter) for manufacturing sectors, covering the period 2005-2018 for 18 Sub-Saharan African countries.

Trade integration through GVCs is strongly related to trade in intermediates. Indeed, two very important indicators of GVC participation are based on foreign value

[52] This area has been said to be the new destination of future offshoring (Baldwin, 2016).

added in exports (FVA or backward integration), which measures imported intermediates embodied in exports, and on domestic value added embodied in exports of intermediates that importers will use to produce exports (IVA or forward integration). These indicators have mainly been used at the country or industry level due to the difficulty of measuring trade in intermediates at the firm level (Kowalski et al., 2015; IMF, 2016; De Melo and Twum, 2021). However, aggregate measures at the country or sector-country level may suffer from a lack of sufficient variability or from aggregation bias due to their dependence on input-output tables. The work of Bems and Kikkawa (2021) focuses on the study of this bias. In particular, they find that sectoral aggregation bias leads to understate the import content of exports. It is the interaction between within-sector heterogeneity in firms' import and export intensities and firm size that explains the magnitude of the bias. Moreover, for Sub-Saharan countries the only source of aggregate measures of GVC participation is the UNCTAD-Eora database, and there are doubts about the quality of these data for some of these countries (especially at the sector level). The lack of some input-output tables has led to missing data being filled in with estimates (Shepherd, 2016).

We therefore believe that a firm-level approach to GVC participation is particularly appealing for Sub-Saharan countries. It can help overcome problems arising from the use of more aggregated data, such as insufficient variability in regression analysis, presence of aggregation biases or the imputation of some data in some countries' input-output tables. Moreover, given that GVC participation is ultimately a firm's internationalisation strategy, there is a growing interest in studies that capture both the determinants and effects of GVC participation at this decision level.

However, the firm-level approach to GVCs is still scarce in the literature. Many firm-level databases do not have information on firm imports or, if they do, they do not

distinguish between imports of intermediate and final goods. The lack of information on imports prevents the calculation of one of the two relevant indicators of GVC participation, the foreign value added in exports (FVA). If there is information on imports but no distinction is made between intermediate and final goods, it has to be assumed that some of them are intermediate inputs. The second indicator of GVC participation, IVA or domestic value added on exports of intermediates imported by exporting firms, requires more assumptions. Most firm-level databases, if they contain information on exports, do not usually distinguish between exports of intermediate and final goods. Therefore, it is often assumed that exporting firms export intermediate inputs that are to be incorporated by importers into their exports. These difficulties (Antràs, 2020) have led to the use of variables such as the two-way trader dummy indicator (which identifies firms that import and export, often without information on whether the goods involved are final or intermediate). Thus, the firm-level literature on GVCs has focused more on the extensive margin of participation (Shepherd and Stone, 2013; Del Prete et al., 2017; Dovis and Zaki, 2020). Our chapter differs from this literature in that we not only use the two-way trader dummy variable (and some extensions adding foreign ownership and/or international certification), but we also approximate the intensive margin of the firm's participation in GVCs. Fortunately, our firm-level database has information on imports of intermediates and exports of goods.[53]

[53] Despite the greater richness of our database, some assumptions still have to be made in the calculation of our GVC-intensive margin measures, as explained in section 3.3 of this chapter. For this reason, we also present a sensitivity analysis of the results when these assumptions are relaxed to some extent. One such assumption, which is robust to relaxation, is that the same mix of input sources (domestic/foreign) is used in domestic sales as in exports. The same proportionality assumption is required in the use of databases from which it is possible to obtain aggregate measures of FVA at country or sector-country level (such as UNCTAD-Eora).

Overall, we believe that the contribution of this chapter is relevant and manifold. First, it provides an in-depth analysis of GVCs in Sub-Saharan Africa from the point of view of firms, whereas previous studies use aggregate country or sector-country level data on GVCs. Second, it jointly considers the effects of a battery of business environment variables on firms' decisions to participate in GVCs. Third, it not only explains firms' participation in GVCs, but also studies its effects on various measures of firm performance (whereas previous studies focus on the determinants or the effects of GVC participation). These include innovation, productivity, wages and employment of firms. Fourth, we use indicators of the extensive and intensive margins of GVC participation, whereas previous work only considers the extensive margin when using firm-level data (Antràs, 2020). Fifth, we consider both backward (FVA) and forward (IVA) integration. Finally, in order to address both the analysis of the determinants and the effects of firms' participation in GVCs, our empirical strategy will take into account that endogeneity may arise.

Our results show that several factors in the business environment affect firms' participation in GVCs. We find that good infrastructure, strict fiscal control possibly signalling quality of institutions and security to prevent crime are conducive to participation. In contrast, difficult access to finance, the existence of an informal sector or high trade costs discourage participation. In terms of outcomes, Sub-Saharan African firms participating in GVCs enjoy superior innovation performance (both in terms of product upgrading and efficiency gains), higher productivity, pay higher wages and generate more employment. Overall, these results hold for all our extensive and intensive measures of GVC participation, including backward (FVA) and forward (IVA) integration. We find an interesting exception that points in the direction that excessive backward integration, i.e. excessive imported input content in exports (as measured by

FVA), may negatively affect incentives for process innovation and, to a lesser extent, the productivity of manufacturing firms in Sub-Saharan Africa.

The chapter is organised as follows. Section 3.2 presents a literature review. Section 3.3 introduces the data and stylised facts. Sections 3.4 and 3.5 describe the methodology used and the results obtained, respectively. Section 3.6 contains a series of robustness checks to strengthen the results. Finally, Section 3.7 concludes.

## 3.2. Literature review

Although the literature on GVCs pays overwhelming attention to country and industry level studies, even at this level of aggregation it remains sparse for African countries. The reason is that the UNCTAD-Eora GVC database is the first to include estimated input-output tables for these countries. Its use led to the first works in the literature to explain the participation of African countries in GVCs. Kowalski et al. (2015) included, among other regions in the world, Eastern and Southern Africa, the Middle East and North Africa, and West and Central Africa. They focused mainly on backward integration (foreign value added, FVA) and did not control for endogeneity. The IMF (2016) study, which focuses on backward integration and includes 185 countries from 2007 to 2011, also uses the UNCTAD-Eora GVC database, but when it comes to Sub-Saharan Africa, sample size restrictions arise. This study controls for endogeneity by including different dummy variables and lagged independent variables.

More recently, Slany (2019) and De Melo and Twum (2021) have also focused on African countries. Slany's (2019) work on regional value chains (RVCs) in 37 African countries uses country-level aggregated data from the UNCTAD-Eora GVC database for the period 2006-2012. In this paper, participation in RVCs is defined by the foreign value added (FVA) content of regional exports, i.e. by regional backward integration. To explain

countries' regional FVA, they include country-level business environment variables among regressors in sequential regressions, as in regressions using country-year data there may be multicollinearity problems due to lower variability at this level of aggregation and sample size limitations (a maximum of 236 observations). This study controls for endogeneity by including country dummies, a time trend and lagged independent variables. The author finds that higher trade costs may hinder the participation of these countries in RVCs. However, the quality of regulation and telecommunication infrastructure can encourage such participation. Despite the focus on regional integration and regional trade in value added among the 37 African countries, as the same author points out, variables affecting RVCs may also be relevant in explaining greater integration in GVCs.

The paper by De Melo and Twum (2021) focuses on Sub-Saharan Africa's participation in GVCs (backward and forward integration) using data at the level of four large regional economic communities: the East African Community, the Economic Community of West African States, the Southern African Development Community, and the Common Market for Eastern and Southern Africa. To our knowledge, their paper is the first to analyse the evolution of GVC participation in Sub-Saharan African countries using Borin and Mancini's (2019) novel dataset on GVC participation measures. De Melo and Twum (2021) use country-year data (or sector-year-country data) on GVC participation that are based on the EORA database. Their work includes, first, a comprehensive descriptive analysis comparing African countries with all countries in the EORA database between 1995 and 2015. Second, it includes the estimation of a GVC equation. At the estimation stage, when the sample is restricted to African countries (with a maximum of 174 observations), the results obtained for the full sample of countries are not reproduced. As the authors argue, sample size may be a problem for these countries.

Despite difficulties at the firm level in measuring participation in GVCs, some studies do so. Nevertheless, this approach is still at a nascent stage, especially in the case of African countries, and more so in Sub-Saharan Africa. This affects both the analysis of the causes and effects of firms' participation in GVCs. Within this literature, we would like to highlight several works focusing on African countries. Dovis and Zaki (2020) use firm-level data from WBES for countries of the Middle East and North Africa (MENA) and East Asia and Pacific (EAP) regions for the period 2006-2017. They propose and use various extensive margin measures of firms' participation in GVCs (depending on whether they import and export, have foreign ownership or are internationally certified). For MENA countries, the authors conclude that the business environment factors relevant for firms' participation in GVCs are mainly the stability of electricity supply, the limitation of the informal sector and the facilitation of access to finance and business procedures. Our work uses the same set of indicators to measure the extensive margin of firms' participation in GVCs. Similarly, we also explain participation with a number of variables from the firms' business environment. However, we differ in the countries analysed and in methodological issues. For example, in their regressions they use business environment indicators at the industry-country level, while we use them at the firm level and instrument them to take into account possible endogeneity. The use of these regressors at the industry-country level reduces their variability and makes multicollinearity problems more likely, which justifies using them one at a time in the regressions to explain firms' participation in GVCs.

Del Prete et al. (2017) also work with firm-level data from WBES for two MENA countries (Egypt and Morocco) in 2004 and 2007. They identify as GVC participating firms those that trade and have an internationally recognised quality certification. Their paper is focused on disentangling whether firms' GVC participation fosters productivity.

For Egypt and Morocco, they obtain that GVC participation has a positive impact on firms' productivity. In the same vein, Ayadi et al. (2020) also find a positive firm-level association between Dovis and Zaki's (2020) GVC indicators and productivity for a broad group of MENA countries. Regarding the labour market effects of GVC participation in developing countries, Shepherd and Stone (2013), using WBES manufacturing firm-level data from 2006 to 2010 for 108 developing and transition countries, show that there is a positive association between GVC participation (firms that import and export or have foreign ownership) and employment and the wages they pay. This may be due to scale and productivity effects resulting from participation in GVCs. On the one hand, when firms export, they should grow and employ more workers. On the other hand, in well-functioning labour markets, traders who increase productivity should pay higher wages. In their paper, they argue that they do not establish a causal relationship, as this would require a different empirical approach, e.g. using instrumental variables. Finally, as regards the effects of participation in GVCs on firms' innovation, Pasquali (2021) used firm-level data from 2006 to 2015 collected by the Kenya Revenue Authority (supplemented by interviews with 17 Kenyan tanneries) to study upgrading of the Kenyan leather sector. They point out that product quality improves when exporting from the South to the North.

In conclusion, not only are studies on firms' participation in GVCs scarce for the African continent (and in particular for Sub-Saharan Africa), but also on how this participation affects innovation, job creation and wages they pay.

### 3.3. Data and stylised facts

The data used in this chapter are mainly from WBES. This database provides firm-level data from surveys of a representative sample of a country's private sector. It produces

internationally comparable data, with homogeneous data sections across countries.[54] Our study includes 18 Sub-Saharan African countries for the years 2005 to 2018.[55] The analysis is based on a pooled dataset, as it is not possible to use panel data with WBES. Surveys are collected every 3-4 years at best and, especially for these countries, it is very difficult to follow the same firms over time. We will work with a sample of 11,060 observations for firms in the manufacturing sectors, although this number may vary according to the different specifications used.[56]

In the following, we describe the three sets of variables used in the chapter: measures of GVC participation, business environment variables to explain GVC participation, and measures of firm performance (innovation, productivity, wages and employment).

### *GVC VARIABLES*

The main variables of interest that we will use throughout the chapter are the different measures of participation in GVCs, which we can divide into two groups. In the first group, we include four measures of firms' internationalisation that capture their extensive margin of participation in GVCs (Dovis and Zaki, 2020). In the second group,

[54] The data were obtained on request from the World Bank. All data can be downloaded free of charge at http://www.enterprisesurveys.org

[55] The countries included in our study and the years for which data are available are: Burundi (2006, 2014), Cameroon (2006, 2009, 2016), Djibouti (2013), Ethiopia (2006, 2011, 2015), Ghana (2007, 2013), Kenya (2007, 2013, 2018), Lesotho (2009, 2016), Madagascar (2005, 2009, 2013), Malawi (2005, 2009, 2014), Mali (2007, 2010, 2016), Mozambique (2007, 2018), Niger (2005, 2009, 2017), Nigeria (2007, 2010, 2014), Rwanda (2006, 2011), Senegal (2007, 2014), Tanzania (2006, 2013), Uganda (2006, 2013) and Zambia (2007, 2013).

[56] The manufacturing sectors are: 1. Food, 2. Garments, 3. Textile, 4. Machinery and Equipment, 5. Chemicals, 6. Electronics, 7. Non-metallic mineral products, 8. Wood, wood products and furniture, 9. Metal and metal products, 10. Other manufacturing.

we include measures of their intensive margin of participation that capture backward and forward integration of firms into GVCs. These intensive margin measures are, respectively, FVA and IVA.

The four measures in the first group range from the simplest GVC concept to a more demanding one. The first will be called "Two-way trader". It implies that the firm imports inputs and exports. The second is "Two-way trader + foreign ownership" and will be called "GVC foreign". It means that the firm is a two-way trader and is owned -or partly owned- by a foreign individual, firm or organisation. Note that GVCs often go hand in hand with foreign direct investment (FDI) inflows (Qiang et al., 2021), as contractual insecurity is particularly relevant for countries with weak institutions. In these countries, foreign MNEs may prefer an organizational structure of production networks that involves intra-firm integration (taking place within firm boundaries). When FDI goes hand in hand with GVCs to guarantee contract enforcement, this points to *relational* GVCs (Antràs, 2020). The third is "Two-way trader + International Certificate" and will be called "GVC certificate". In this case, the firm is a two-way trader and it has an internationally-recognised quality certification. Participation in GVCs normally requires compliance with global quality standards (Del Prete et al., 2017). The fourth and last is the strictest. It includes all of the above, so the firm is a two-way trader, has foreign participation and holds an international certificate. It will be "Two-way trader + Foreign ownership + International Certificate", and will be called "GVC all". All these indicators are dummy variables that take the value 1 if the firm participates in GVCs and 0 otherwise.

The measures in the second group capture two different aspects of participation in GVCs: Foreign Value Added embodied in gross exports (FVA) and Indirect Value Added (IVA). FVA refers to the value added of inputs that were imported to produce intermediate

or final goods that are exported, or in other words, the content of intermediate imports embodied in exports.[57] It is a measure of "Backward integration" and also of "Downstream participation".[58] IVA (which can also be found in the literature as DVX) is the domestic value added contained in intermediate products exported to a partner economy that re-exports them to a third economy incorporated into other products. In other words, it is the domestic value added contained in inputs sent to third economies for further processing and export through value chains. It is a measure of "Forward integration" and also of "Upstream participation" (World Trade Organization, 2019).[59] In this chapter we calculate FVA and IVA for each firm with the information available in WBES.

To construct FVA, the value of imported intermediate inputs has first been obtained from the percentage of foreign intermediates applied to the value of the firm's total intermediates. Next, it has been assumed that imported intermediate inputs are allocated proportionally to the firm's total sales.[60] Thus, we have finally obtained the value of imported intermediate inputs that are incorporated into exports as:

[57] Note that a positive value of FVA implies a value 1 for the dummy variable "Two-way trader", as this dummy variable takes value 1 when a firm that imports intermediate goods also exports (either intermediate or final goods).

[58] FVA is an indicator of the firm's backward integration into the GVC, which also indicates that the firm is closer to the final consumer than its international input suppliers, i.e. it has a more downstream position in the GVC than they do.

[59] IVA is an indicator of the firm's forward integration into the GVC, which also indicates that the firm is further away from the final consumer than its international input importers, i.e. it has a more upstream position in the GVC than they do. It has been argued that, using firm-level data, constructing a measure of IVA is more difficult than FVA (Antràs, 2020), so an effort will be made to make the measure as accurate as possible.

[60] This assumption implies that the proportion of foreign inputs is equally spread between exports and domestic sales. However, we will conduct a sensitivity analysis of this assumption in section 3.6 of the chapter. This proportionality assumption will be relaxed but replaced by another assumption. We will assume that for exporters the share of foreign inputs in domestic sales is the same as the average for non-exporting firms in the same sector-country-year. With the original assumption, the average FVA is 0.022 and with its relaxation it is higher (0.039). This is consistent with a higher share of imported inputs in exports than in domestic sales (Ahmad, 2013; Slany, 2019).

$$Value\ of\ imported\ intermediate\ inputs\ in\ firm's\ exports =$$

$$= \frac{Value\ of\ imported\ intermediate\ inputs\ * Firm's\ exports}{Firm's\ Sales}$$

FVA is then calculated as this value normalised by the firm's exports:

$$FVA = \frac{Value\ of\ Imported\ Intermediate\ Inputs\ in\ firm's\ Exports}{Firm's\ Exports}$$

To construct IVA, we have first calculated the domestic value added as follows:

$$Domestic\ Value\ Added = Firm's\ Sales - Value\ of\ firm's\ intermediate\ imports$$

We also assume that the percentage of Domestic Value Added Exported is the same as the percentage of Domestic Value Added in the firm's total Sales.[61] With this assumption, we can calculate the Domestic Value Added Exported and thus the IVA as follows (after normalising the Domestic Value Added Exported by the firm's exports):

$$IVA = \frac{Domestic\ Value\ Added\ Exported}{Firm's\ Exports}$$

Note that with this measure we have not taken into account part of the definition of IVA. As mentioned above, IVA is the domestic value added contained in intermediates exported to a partner economy that re-exports them to a third economy incorporated in other products. However, we have not been able to fully account for the latter. This is because this information is rarely available in databases derived from enterprise surveys, including WBES. In fact, we are not aware of any enterprise survey that contains this information. Still, we can reasonably assume that, in a globalised world, firms exporting

[61] We can relax this assumption by assuming that for exporters the proportion of Domestic Value Added in domestic sales is the same as the average for non-exporting firms in the same sector-country-year. If we relax the original proportionality assumption in this way, the average value of IVA is slightly reduced (from 0.102 to 0.096). This is consistent with a smaller share of Domestic Value Added in exports than in domestic sales. In section 3.6, we also perform a sensitivity analysis to this assumption.

intermediate inputs are likely to be engage in "forward integration" (i.e. they have a positive IVA value). The reason is that firms that import intermediates are often also exporters (Gal and Witheridge, 2019; Antràs, 2020). Note also that IVA will not be calculated for firms in all manufacturing sectors, but only for those belonging to sectors producing mainly intermediate goods. [62] This is because WBES does not distinguish between exports of final or intermediate goods (information which is often missing also in enterprise surveys). Therefore, since IVA refers to the domestic value added contained in exported intermediates, we borrow here an idea from studies with sectoral data, where IVA is only calculated for sectors that can be reliably assumed to produce mainly intermediate inputs (this was first suggested in Yeats, 1998).

The descriptive statistics of our data are similar to those of other African countries. Therefore, for the set of GVC indicators already in Dovis and Zaki (2020) results are comparable. We obtain that 15% of firms are two-way traders, 5% are two-way traders with foreign ownership, 5% are two-way traders with international certificate and only 2% are two-way traders with foreign ownership and international certificate. Furthermore, for FVA it is relevant to note that there is a 2.5% content of intermediate imports embodied in exports, which is a value consistent with Amendolagine et al. (2019) using the African Investor Survey. Finally, the domestic value added contained in exported intermediate products is around 11% (IVA). As expected in resource-abundant countries (World Bank, 2020a), Sub-Saharan African firms participate more through IVA. This indicates that, on average, they are more involved in upstream participation (forward

[62] The manufacturing sectors that correspond to intermediate goods according to the Standard International Trade Classification (SITC) of the United Nations (UNIDO, 2011) are: 1. Textile, 2. Chemicals, 3. Electronics, 4. Non-metallic mineral products, 5. Wood, wood products and furniture, 6. Metal and metal products.

integration into GVCs). They are therefore involved in activities closer to the primary sector and further away from the final consumer than their importers. This evidence has been supported by previous research highlighting that not only is forward integration more important for these countries, but it is also the region with the highest forward integration in the world (De Melo and Twum, 2021).

In any case, although their presence has grown, the general perception emerging from the descriptives is that there are still not many Sub-Saharan African firms participating in GVCs (AfDB, OECD, UNDP, 2014). Nevertheless, participation is not evenly distributed among the different countries of study. Firms in Cameroon and Kenya are the largest participants, with an average participation rate twice that of Sub-Saharan Africa. In Cameroon, almost 31% of firms are two-way traders, the content of intermediate imports embodied in exports is 7.5% and the domestic value added contained in exported intermediate products is about 32%. In Kenya these figures are 34.5%, 6.4% and 39% respectively. This is not by chance, since both countries are doing an effort to consolidate their industrialisation. The Kenyan government, for example, has lauched the “National Industrialization Policy Framework for Kenya 2012–2030” with the aim of transforming Kenya into a globally competitive regional industrial hub (Todorov, 2020). In contrast, firms in Ethiopia and Nigeria hardly participate in GVCs. Their average participation is half the average for the region. In Ethiopia, 9.6% of firms are two-way traders, the content of intermediate imports embodied in exports is 1.7% and the domestic value added contained in exported intermediate products is 2.3%. In Nigeria, these figures are 6%, 0.6% and 6.4% respectively.

As with countries, not all sectors have the same participation rates. The textile sector is among top participants. In this sector, 33.5% of firms are two-way traders, the content of intermediate imports embodied in exports is 5.6% and the domestic value

added contained in exported intermediate products is about 25%. The textile and garment sectors have played a key role in the industrialisation of many countries since the Industrial Revolution, and Sub-Saharan African firms have the potential to be competitive in these sectors (US International Trade Commission, 2009; Yülek and Yağmur, 2018; World Bank, 2020a). For this reason, the African Development Bank has launched "Fashionomics Africa", which aims to stimulate the sector and help African firms capture more value within GVCs (Fashionomics Africa, 2021). Slany (2019), using sector-level data from UNCTAD-Eora database, corroborates the importance of this sector and also highlights the relevance of the transport equipment sector when it comes to backward integration in GVCs. The same is true for our data. Therefore, our firm-level measures detect the same leading sectors as the more aggregated ones. Moreover, both sectors have been highlighted in the literature for their upgrading potential within the value chain. This is why they are on the agenda of the African Union's Plan of Action for Accelerated Industrial Development of Africa.

### *BUSINESS ENVIRONMENT VARIABLES*

Business environment factors can help or hinder firms' participation in GVCs. Infrastructure, labour conditions, financial facilities, taxes, trade procedures or permits, the informal sector or criminality are some of the aspects that can influence this decision (see World Bank, 2020a, for a review of business environment factors that can drive participation in GVCs).

Investment in infrastructure is key to fostering a country's growth and economic progress. It is a key element for African countries. In fact, half of the continent's recent economic growth is due to infrastructure investment (Moller and Wacker, 2017; African Development Bank Group, 2022). In addition, good infrastructure is crucial for boosting

trade (Button, 2002). Lack of basic infrastructure, such as electricity or water, affects some African countries and can become a major obstacle to their growth and participation in trade. Good communication services are also part of a country's essential infrastructure to stay on the path to growth and internationalisation. Along these lines, there is some recent work on the role of telecommunications infrastructure (in particular, the submarine fibre-optic cable) in international connectivity (Cariolle, 2021) and trade (Sun, 2021; Imbruno et al., 2022). Sub-Saharan countries are making efforts to improve infrastructure, which is reflected in official statistics. For example, the rising values of the Africa Infrastructure Development Index (African Development Bank Group, 2020) are evidence of their progress.

Another major obstacle faced by many developing countries, especially in Africa, is the lack of financial facilities. There seems to be a lack of medium-term financing, capital markets are rudimentary and financial intermediation is rather weak (Kounouwewa and Chao, 2011). Not only that, but regulatory environments are seen as predatory, causing firms to seek escape routes to avoid the burden of regulation. This makes access to formal finance more difficult and forces informal financing of firms. Since better access to bank financing increases the likelihood that firms will export (Abora et al., 2014), failure to ensure this may harm their participation in GVCs. Furthermore, with regard to labour conditions and tax policy, participation in GVCs may require flexible and uncomplicated regulations and procedures that allow for fast adjustment when necessary. Similarly, trade procedures or permits may also affect trade flows of intermediate inputs, as they also affect trade costs through price increases or customs delays. To sum up, if regulation imposes an excessive burden on developing country firms, there is a risk that the informal sector will grow, making it difficult for them to integrate into GVCs.

Another severe problem on the African continent that may be interfering with its development is criminality. It can be seen as an economy-wide tax that discourages foreign direct investment (Detotto and Otranto, 2010) and thus participation in GVCs. Quality of governance and institutions can also be a problem, as all Sub-Saharan African countries are below the 50th percentile of the World Governance Indicators. Although the situation has been improving over the years, it is still worrying (World Bank, 2020b). Low quality of governance may prevent firms from these countries from participating in GVCs.

In this chapter, we will use a number of business environment variables that may influence firms' participation in GVCs. These variables capture different aspects of the business environment, such as infrastructure, labour conditions, financing, taxation, informality, trade procedures and security. Table A3.1 in the Appendix 3 contains the detailed definition of each of these variables and their sources. Most of them come from WBES, but there are two at the country level that come from the World Bank's Doing Business. Those related to infrastructure are suffering power outages (outage), owning a generator (generator) and using website (web), while labour regulation as an obstacle (average obst labour) and skill intensity are those related to labour conditions. Access to finance as an obstacle (obst finance) is the measure for financing, and tax rate as an obstacle (tax obst) and the presence of tax inspection correspond to taxation. Moreover, it is taken into account whether the informal sector is an obstacle (informality) and whether firms have to pay to ensure their safety (security). Finally, import cost and export days refer to trade procedures.[63]

[63] These are the two World Bank's Doing Business variables.

In Table 3.1, we report the mean and the standard deviation of these variables, distinguishing between GVC participants and non-participants. As the figures show, the percentage of firms that own a generator, use a website, receive tax inspections or pay for security is higher if they participate in GVCs. Nevertheless, the percentage of firms that say that financing or informality is a barrier is higher if they do not participate in GVCs. This descriptive analysis can give us an idea of the business environment factors that might be behind firms' participation in GVCs.

Table 3.1. Descriptive statistics – Business environment variables

| | **GVC Participation** | |
|---|---|---|
| | YES | NO |
| **OUTAGE** | 0.895 - 0.838<br>(0.307 - 0.370) | 0.856 - 0.843<br>(0.351 – 0.364) |
| **GENERATOR** | 0.798 - 0.692<br>(0.402 - 0.462) | 0.512 - 0.482<br>(0.500 – 0.500) |
| **WEB** | 0.756 - 0.467<br>(0.430 - 0.499) | 0.205 - 0.153<br>(0.404 - 0.360) |
| **SKILLED INTENSITY** | 47.846 - 44.905<br>(25.809 - 26.031) | 58.369 – 57.536<br>(27.625 – 28.196) |
| **AVERAGE OBST LABOUR** | 0.012 - 0.007<br>(0.023 - 0.015) | 0.008 – 0.005<br>(0.017 - 0.013) |
| **OBST FINANCE** | 0.132 - 0.061<br>(0.339 - 0.240) | 0.256 - 0.218<br>(0.437 - 0.413) |
| **TAX INSPECTION** | 0.888 - 0.800<br>(0.316 - 0.400) | 0.749 - 0.740<br>(0.434 - 0.438) |
| **OBST TAX** | 0.112 - 0.097<br>(0.316 - 0.297) | 0.082 - 0.072<br>(0.275 – 0.259) |
| **INFORMALITY** | 0.118 - 0.096<br>(0.323 - 0.296) | 0.144 - 0.127<br>(0.351 - 0.333) |
| **SECURITY** | 0.904 - 0.791<br>(0.296 - 0.407) | 0.643 - 0.621<br>(0.479 - 0.485) |
| **IMPORT COST** | 3.444 - 3.199<br>(1.673 - 1.683) | 3.290 - 3.113<br>(1.954 - 1.931) |
| **EXPORT DAYS** | 30.726 - 28.462<br>(9.640 - 8.768) | 30.08 - 29.440<br>(11.150 - 10.463) |

Notes: (i) Standard deviation in parenthesis. (ii) Columns called “yes” correspond to GVC participants, and “no” to nonparticipants. (iii) We represent the range of values for all types of GVC participation.

*PERFORMANCE VARIABLES*

Once potential barriers are overcome, firm participation in GVCs can have positive effects on firm performance measures (Kowalski et al., 2015). One of the main expected benefits is improved productivity. There are several channels through which this can occur. If a firm participates in GVCs it can reduce input costs or expand the scale of production (Antràs, 2020). It can also benefit from a wider dissemination of knowledge and specialise further in its core activities or in higher value-added tasks (Criscuolo and Timmis, 2017).

Moreover, firms participating in GVCs may create more jobs and pay higher wages, although the literature on developing countries is inconclusive in this regard (Farole, 2016). First, formal jobs are expected to be created in the manufacturing sector and demand for low-skilled, labour-intensive jobs is also likely to increase (Shepherd, 2013). However, if participation in GVCs leads to a shift towards more skilled or capital-intensive activities, job creation could be in doubt (Banga, 2016). In addition, if the reason for developed countries' interest in African manufacturing is access to abundant low-skilled labour, a wage differential in these countries in favour of workers in globalised firms may be due to their greater ability to pay higher wages and the fact that their workers have more and better physical capital at their disposal (Bernard et al., 2018).

Another potential benefit of participation in GVCs is the increased innovation of firms. Some studies have shown that certain firms are more successful at innovating, but this is only the case if the firm participates in GVCs as a highly qualified supplier (Brancati et al., 2017). Others suggest that it can encourage innovation and technological upgrading, especially in developing countries (Shepherd, 2015). These countries need to meet product quality, delivery time, process efficiency, environmental friendliness, and

labour and social standards required by GVCs, which may force them to innovate (Pietrobelli and Rabellotti, 2011). Furthermore, participation in GVCs involves not only flows of goods and materials, but also of intangibles such as information, technology or managerial knowledge (Timmer, 2017; Antràs, 2020). This can also lead to greater innovation. Nevertheless, it may also be the case that firms in developing countries prefer to acquire foreign technology from advanced economies rather than innovate (Fu et al., 2011).

In this chapter, we are interested in three variables related to innovation: the R&D decision, the launch of a new product and the introduction of a new process. The first one is related to innovation inputs, while the last two are related to innovation outputs (they refer to quality upgrading or efficiency improvement, respectively). We are also interested in three variables related to firms' workers: the number of workers, their productivity and wages.[64]

Figures 3.1-3.6 represent the mean of the different performance measures considered, distinguishing between participants and non-participants according to different definitions of GVC participation.[65] Means are always higher for GVC participants. Thus, firms participating in GVCs innovate more, pay higher wages, have higher labour productivity and have more workers. This descriptive analysis indicates some potential benefits that can be derived from participation in GVCs.

[64] Productivity can also be included among innovation variables, since it can incorporate efficiency improvements resulting from innovation.

[65] Table A3.2 in Appendix 3 shows the definitions of the performance measures considered. While innovation variables (R&D decision, New product and New process) are dummy variables, employment-related variables (Labour productivity, Wages and number of Workers) are continuous variables expressed as the ratio of the firm's value over the country-sector-year average.

Figures 3.1. – 3.6. Means of the variables distinguishing between participants and nonparticipants in GVCs.

Figure 3.1

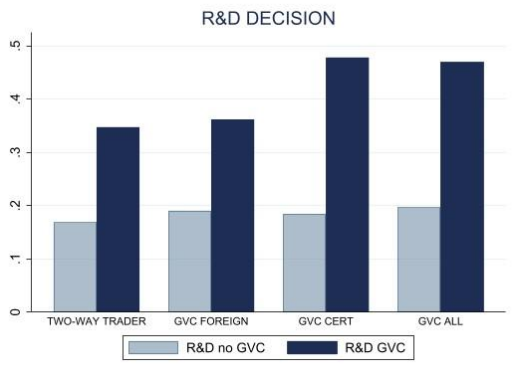



Figure 3.2

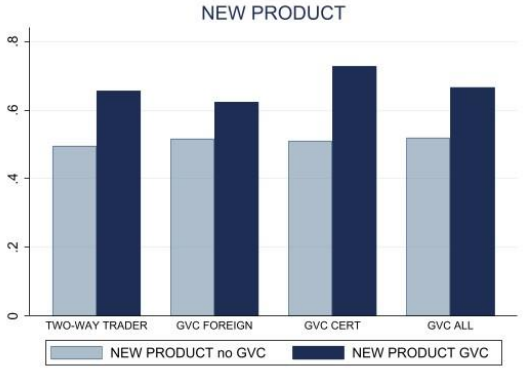



Figure 3.3

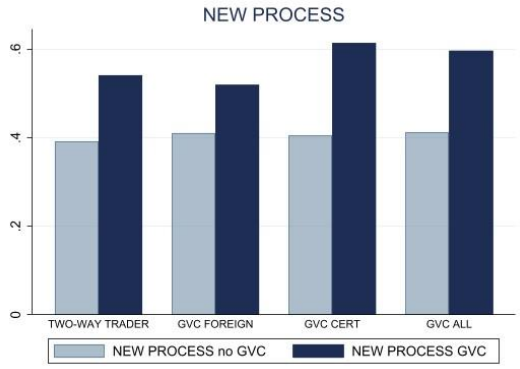



Figure 3.4

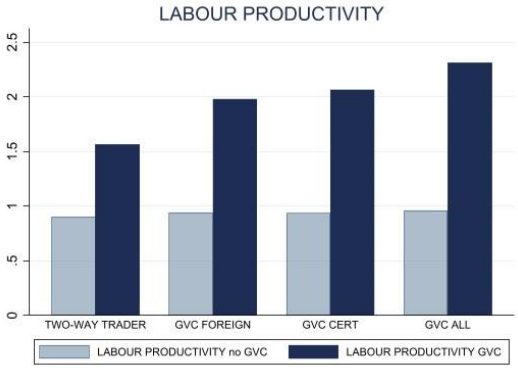



Figure 3.5

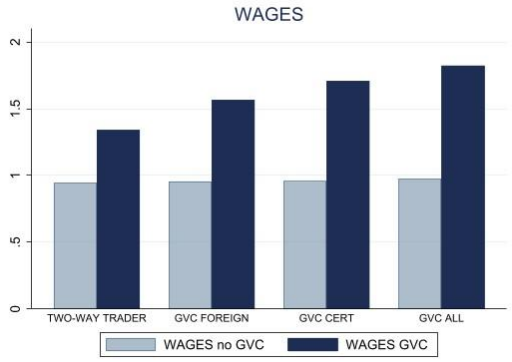
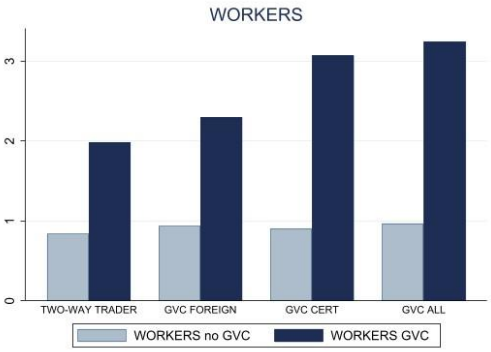



Figure 3.6



## 3.4. Methodology

In this section, we introduce the econometric specifications and methodology for estimating the equations for firms' participation in GVCs and those for its effect on different measures of firm performance. First, we specify the GVC participation equation. For our four discrete GVC measures, we use the following probit model:[66]

$$Prob\ (GVC) = \begin{cases} 1\ if\ \beta_0 + \beta_1 BE + \beta_2 X + \delta_c + \delta_j + \delta_t + \varepsilon > 0 \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{3.1}$$

where $BE$ refers to the vector of business environment variables, $X$ is the vector of control variables including age and firm size and $\delta_c, \delta_j, \delta_t$ are country, sector and year fixed effects.[67]

The two remaining GVC variables (FVA and IVA) are continuous, but with a considerable amount of zeros because many firms do not participate in GVCs. For them we will use a Tobit model whose specification is as follows:

$$GVC = \beta_0 + \beta_1 BE + \beta_2 X + \delta_c + \delta_j + \delta_t + \varepsilon \tag{3.2}$$

Due to the pooled dataset nature of WBES, we have controlled in estimation for confounding factors using firm-level characteristics such as size and age. Moreover, we have included a set of fixed effects to absorb unobserved heterogeneity at the country, sector and year level. Nevertheless, some business environment indicators measured at the firm level may be endogenous.

[66] The GVC variables that are discrete are: "Two-way trader", "GVC foreign", "GVC certificate" and "GVC all".

[67] $BE$ includes the business environment variables mentioned above: suffering power outages, owning a generator, using website, skills intensity, labour as an obstacle, finance as an obstacle, tax inspection, tax rate as an obstacle, informality, security, import cost and export days. Age is introduced in logarithm, and size is a dummy that takes the value one if the firm has more than 100 employees and zero otherwise.

To address this issue, we allow firm-level decisions, such as investing in a generator, website, worker skills, and firm security, to be endogenous. We also treat as potentially endogenous the regressor on whether the biggest obstacle faced by the firm is access to finance, as belonging to a GVC may alleviate firms' financial constraints.[68] Our IVs strategy for estimating the four discrete dependent variables of GVC participation (characterised by equation (3.1) above) consists of estimating the joint likelihood function of each dependent variable and the potentially endogenous regressors (limited information maximum likelihood –LIML). Since each regressor suspected of being endogenous has as external instrument its own mean value at the country-sector-year level (subtracting the individual firm's own response), the IV method is just identified. The endogeneity tests for the regressors generator, website, skill intensity, obstacle finance and security are classical LIML-based tests, with null hypothesis of zero correlation between the unobservables in the equation of interest (each of the four discrete GVC indicators) and the unobservables in the equations for the potentially endogenous regressors. Estimation is performed with the user-written Stata command *cmp* developed by Roodman (2011).[69]

Our extension to instrumental variables of the Tobit model in equation (3.2), which is applied to the two remaining censored GVC variables, "FVA" and "IVA", follows a

[68] All regressors treated as potentially endogenous are WBES firm-level regressors. The others are country-level regressors from the World Bank's Doing Business (such as import cost and export days), or from the WBES but more intrinsically related to the business environment in which firms operate (such as obstacles they face related to labour regulation, presence of the informal sector in the economy and fiscal policy pressure, or other factual factors such as the existence of power outages and the quality of the tax authority and the tax system).

[69] cmp estimates multi-equation mixed process models, where "mixed process" means that different equations in the joint likelihood function can have different kinds of dependent variables (for instance, continuous like in OLS, censored like in tobit, and binary like in probit). In our application of the cmp command for instrumenting the estimation of equation (3.1), all dependent variables in the joint likelihood function are binary, except for skill intensity (which is a continuous variable representing the percentage of skilled workers).

simple control function approach (Rivers and Vuong, 1988), as suggested by Wooldridge (2015). It proceeds in two steps. First, we obtain the generalised residuals of a probit when the potentially endogenous regressors are binary or the OLS residuals when they are continuous. Second, we add them as explanatory variables in the Tobit equation. Their statistical significance in this equation is an optimal test for rejecting the null hypothesis that potentially endogenous regressors are exogenous, and their inclusion corrects for endogeneity problems. The reason why with censored dependent variables, such as FVA and IVA, we do not estimate the joint likelihood function of the dependent variable and the potentially endogenous regressors is that numerical integration is more demanding and generates computational problems and lack of convergence.

Our next step in the chapter is to analyse the effects of firms' participation in GVCs on selected performance measures. We consider six different dependent variables, three on innovation and three related to labour. The innovation variables are whether to invest in R&D, the introduction of a new product and the introduction of a new process. The labour-related variables are labour productivity, wages and the number of workers.

Due to the different nature of dependent variables, two types of models have to be estimated. For binary choice variables (such as innovation variables), we use a probit model. For labour-related variables, which are continuous, we use linear regression. Thus, for innovation variables we specify:

$$Prob\ (INNOV) = \begin{cases} 1\ if\ \beta_0 + \beta_1 GVC + \beta_2 X + \delta_c + \delta_j + \delta_t + \varepsilon > 0 \\ 0\ otherwise \end{cases} \quad (3.3)$$

In addition, for labour-related variables:

$$EMPLOYM = \beta_0 + \beta_1 GVC + \beta_2 X + \delta_c + \delta_j + \delta_t + \varepsilon \quad (3.4)$$

where the explanatory variable $GVC$ refers to the different definitions of GVCs used in the chapter, $X$ is a vector of control variables including age and firm size, and $\delta_c, \delta_j, \delta_t$ are country, sector and year fixed effects.

To correct for possible endogeneity of GVC measures in these regressions, we first apply an IV strategy. Second, we apply a propensity score matching method as an alternative, the results of which can be found in the robustness checks section of the chapter. As for these performance equations numerical integration is not a problem because of the smaller dimension of the integrals involved, the IV strategy consists again in estimating a joint likelihood function for each dependent variable and the potentially endogenous GVC indicator (limited information maximum likelihood –LIML). Estimation is performed with the user-written Stata command *cmp* developed by Roodman (2011), which allows mixing variables of different nature (continuous as in OLS, censored as in tobit, and binary as in probit) into a single likelihood function. For each GVC indicator selected as regressor in the performance equations, we perform three instrument-related tests. The first tests correlation between the error in the performance equation and the error in the GVC equation. This is the endogeneity test with null hypothesis of zero correlation. The second tests the joint significance of IVs in the equation that instruments a particular GVC indicator. Its null hypothesis is that instruments have no explanatory power on the GVC indicator they are instrumenting. The third test is to determine whether, once the GVC indicator is instrumented, all instruments (excluding one) can be excluded from the performance equation (equation of interest). This test has the null hypothesis of joint exclusion of IVs in that equation. The potential instrumental variables are those that are used to explain firms' participation in GVCs. From this set, IVs are selected in each case on the basis of the conditions required for

their validity. These are to have explanatory power on the instrumented GVC indicator but no effect on the performance equation of interest (once already used as instruments).

With the alternative propensity score matching methodology we compare a treated group (firms belonging to a GVC) with a control group (firms that do not belong to a GVC but have similar characteristics). We consider four different treatments corresponding to our dichotomous measures of GVC participation "Two-way trader", "GVC foreign", "GVC certificate" and "GVC all". In a first step, we run four probit models based on equation (3.1) to obtain the different predicted probabilities (propensity scores) of belonging to a GVC. In a second step, we use Mahalanobis metric matching with propensity scores to match participants and non-participants in GVCs.[70] As the performance of different matching techniques can be data specific, our selected propensity score matching technique is the one that balances all probit covariates between participants and non-participants. This indicator of matching quality is based on the difference in covariate means between the treatment and control groups, as well as on joint measures of covariate balance. Finally, the implemented propensity score matching method also keeps all treated observations on common support.

## 3.5. Empirical results

*BUSINESS ENVIRONMENT FACTORS DETERMINING PARTICIPATION IN GVCs*

The estimation results of the model in (3.1) for the discrete GVCs dependent variables are in Table 3.2.1. At the bottom of this table, we provide the endogeneity tests for the potentially endogenous regressors. According to the results of these tests, there are no endogenous regressors in the "Two-way trader" and "GVC certificate" equations.

[70] The procedure is performed in Stata, using the psmatch2 routine developed by Leuven and Sianesi (2003).

However, *obstacle finance* and *security* are endogenous in the equations "GVC foreign" and "GVC all". Moreover, in the equation "GVC foreign" also turns out to be endogenous *generator*.[71, 72] Also at the bottom of Table 3.2.1. we show the IV statistical significance for each endogenous regressor. This is the estimated marginal effect and the statistical significance of the corresponding instrument in each endogenous regressor equation (where explanatory variables are the exogenous regressors in equation (3.1) plus the instrument). Finally, the estimation results of the model in (3.2) for the continuous GVC indicators FVA and IVA can be found in Table 3.2.2. The endogeneity tests at the end of Table 3.2.2. indicate that there are no endogeneity problems for these cases.

Table 3.2.1 Estimated marginal effects –Business environment factors determining participation in GVCs (IV strategy instrumenting potentially endogenous regressors with its means).

| VARIABLES | (1) TWO-WAY TRADER | (2) GVC FOREIGN | (3) GVC CERTIFICATE | (4) GVC ALL |
|---|---|---|---|---|
| **Outage** | -0.013 | -0.032** | -0.000 | -0.022*** |
| | (0.021) | (0.013) | (0.008) | (0.009) |
| **Generator** | 0.055*** | 0.098*** | 0.029*** | 0.010** |
| | (0.010) | (0.023) | (0.005) | (0.005) |
| **Web** | 0.111*** | 0.031*** | 0.069*** | 0.035*** |
| | (0.012) | (0.011) | (0.008) | (0.006) |
| **Skilled intensity** | -0.001** | -0.000† | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **Average obst labour** | -0.571*** | -0.099 | -0.212* | -0.048 |
| | (0.183) | (0.156) | (0.124) | (0.128) |
| **Obst finance** | -0.036*** | -0.095*** | -0.009 | -0.035** |
| | (0.014) | (0.028) | (0.006) | (0.017) |
| **Tax inspection** | 0.021* | -0.007 | 0.016*** | 0.008** |
| | (0.012) | (0.014) | (0.005) | (0.003) |
| **Obst tax** | -0.027** | -0.033* | -0.004 | -0.013 |
| | (0.011) | (0.019) | (0.010) | (0.013) |
| **Informality** | -0.038*** | -0.013 | -0.015** | -0.010* |
| | (0.012) | (0.009) | (0.006) | (0.005) |
| **Security** | 0.044*** | 0.114*** | 0.018*** | 0.039*** |
| | (0.015) | (0.029) | (0.004) | (0.012) |
| **Import cost** | -0.013** | -0.017*** | -0.001 | -0.003 |
| | (0.006) | (0.006) | (0.002) | (0.003) |
| **Export days** | -0.016*** | -0.006*** | -0.000 | -0.001 |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| **size** | 0.133*** | 0.042*** | 0.049*** | 0.025*** |
| | (0.009) | (0.010) | (0.005) | (0.005) |

[71] The estimated marginal effects for equation (3.1) in Table 3.2.1. come from instrumenting those regressors that, according to the tests, are indeed endogenous. In this way, we increase efficiency.
[72] Endogeneity problems seem to arise when the definition of GVC participation includes foreign capital.

| | | | | |
|---|---|---|---|---|
| **Log age** | 0.010 | -0.014 | 0.017*** | 0.006* |
| | (0.009) | (0.009) | (0.002) | (0.003) |
| **Constant** | 3.249*** | 1.300 | -2.849*** | 2.212*** |
| | (0.614) | (0.951) | (0.717) | (0.520) |
| Observations | 8,749 | 8,676 | 8,661 | 8,590 |
| **Endogeneity tests: Correlation between the error of each GVC equation and the errors of the equations of the potentially endogenous regressors** | | | | |
| Generator | -0.165 | -0.387*** | 0.157 | -0.042 |
| | (0.242) | (0.081) | (0.169) | (0.292) |
| Web | -0.034 | 0.039 | -0.004 | -0.128 |
| | (0.190) | (0.267) | (0.165) | (0.141) |
| Skilled intensity | 0.437 | 0.024 | 0.443 | -0.143 |
| | (0.419) | (0.394) | (0.479) | (0.556) |
| Obst finance | -0.070 | 0.390* | 0.113 | 1.008* |
| | (0.198) | (0.223) | (0.149) | (0.583) |
| Security | -0.322 | -0.592*** | -0.219 | -0.353** |
| | (0.269) | (0.226) | (0.231) | (0.175) |
| **Endogenous regressor (its IV statistical significance)** | | | | |
| $Generator_i$ (Mean $(Generator_{cjt})^{-i}$) | | 0.430*** | | |
| | | (0.054) | | |
| $Obst\ finance_i$ (Mean $(Obst\ finance_{cjt})^{-i}$) | | 0.297*** | | 0.318*** |
| | | (0.065) | | (0.066) |
| $Security_i$ (Mean $(Security_{cjt})^{-i}$) | | 0.305*** | | 0.289*** |
| | | (0.068) | | (0.065) |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1, † slightly above 0.1. (iii) All regressions control for country, sector and year dummies. (iv) For the equations instrumenting the endogenous regressors, explanatory variables are the exogenous variables in equation (3.1) plus the respective instrument of each endogenous regressor. The instrument of a given endogenous regressor is the mean of this regressor calculated with all firms in the same country, industry and year than firm *i*, excluding firm *i*. (v) To increase efficiency, the estimated marginal effects for equation (3.1) shown in this table come from instrumenting those regressors that, according to the tests, are effectively endogenous.

Table 3.2.2. Estimated marginal effects –Business environment factors determining participation in GVCs (IV strategy instrumenting potentially endogenous regressors with its means).

| **VARIABLES** | **(1) FVA** | **(2) IVA** |
|---|---|---|
| **Outage** | 0.006 | -0.099 |
| | (0.069) | (0.118) |
| **Generator** | 0.157*** | 0.233*** |
| | (0.033) | (0.066) |
| **Web** | 0.239*** | 0.381*** |
| | (0.051) | (0.115) |
| **Skilled intensity** | -0.002** | -0.002* |
| | (0.001) | (0.001) |
| **Average obst labour** | -1.241** | 1.568 |
| | (0.530) | (3.103) |
| **Obst finance** | -0.102* | -0.200** |
| | (0.054) | (0.102) |
| **Tax inspection** | 0.093** | 0.118† |
| | (0.040) | (0.076) |
| **Obst tax** | -0.100** | -0.099 |
| | (0.044) | (0.095) |
| **Informality** | -0.107** | -0.205* |
| | (0.050) | (0.105) |
| **Security** | 0.155*** | 0.123† |
| | (0.047) | (0.078) |
| **Import cost** | -0.043*** | -0.131** |
| | (0.015) | (0.065) |
| **Export days** | -0.038*** | -0.086*** |
| | (0.007) | (0.016) |

| | | |
|---|---|---|
| **size** | 0.374*** | 0.562*** |
| | (0.058) | (0.107) |
| **Log age** | 0.053** | 0.093† |
| | (0.023) | (0.060) |
| **Constant** | 1.139** | 3.607*** |
| | (0.342) | (0.944) |
| Observations | 8,561 | 3,573 |
| **Endogeneity tests: Correlation between the error of each GVC equation and the errors of the equations of the potentially endogenous regressors** | | |
| Generator | -0.052 | 0.143 |
| | (0.142) | (0.298) |
| Web | 0.244 | 0.575 |
| | (0.179) | (0.565) |
| Skilled intensity | 0.008 | 0.020 |
| | (0.007) | (0.014) |
| Obst finance | -0.047 | 0.343 |
| | (0.132) | (0.301) |
| Security | -0.008 | 0.392 |
| | (0.160) | (0.328) |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1, † slightly above 0.1. (iii) All regressions control for country, sector and year dummies. (iv) For the equations instrumenting the endogenous regressors, explanatory variables are the exogenous variables in equation (3.1) plus the respective instrument of each endogenous regressor. The instrument of a given endogenous regressor is the mean of this regressor calculated with all firms in the same country, industry and year than firm *i*, excluding firm *i*. (v) To increase efficiency, the estimated marginal effects for equation (3.2) shown in this table come from instrumenting those regressors that, according to the tests, are effectively endogenous.

As results show, several business environment variables have a significant impact on GVC participation (extensive margin) and GVC deepening (intensive margin). To begin with, infrastructure variables have a rather homogeneous qualitative effect on the different measures of GVCs. Although suffering a power outage is only statistically significant for the dichotomous indicators GVC foreign and GVC all, in the other cases it still shows a generally negative sign, which is to be expected. Furthermore, having a generator or a website always has a positive and significant effect. Our results show the importance of a good infrastructure that includes both basic elements (such as electricity) and communication (Baghdadi and Guedidi, 2021, show that internet adoption boosts African countries' participation in GVCs).

Moreover, when labour regulation as an obstacle is statistically significant, it has a negative impact on GVC measures (see Two-way trader, GVC certificate and the tobit equation “FVA”). On the other hand, skill intensity has a significant negative effect in most cases. This implies that having a higher skill intensity reduces the probability of

participating in GVCs or, in terms of the results of the tobit equations, that it decreases FVA and IVA. This may be because firms are outsourcing labour-intensive stages of production to areas with low labour costs, such as Sub-Saharan Africa. These stages often require unskilled labour (Bottini et al., 2007). This is consistent with "skilled-labour abundant countries benefit from importing low-skill-labour intensive goods from low-skill labour abundant economies" (Antràs, 2020). In other words, as Sub-Saharan African countries are unskilled labour abundant, they can specialise in stages of production that are unskilled labour intensive (Heckscher-Ohlin theory).

Similarly, access to finance as an obstacle significantly reduces participation and deepening in GVCs. This finding is similar to other work on Africa, which finds that access to finance is a major barrier (Fowowe, 2017). Tax rates as an obstacle are only statistically significant in the case of the indicators Two-way trader, GVC foreign and the tobit equation "FVA", although in all other cases they still maintain their expected negative sign. In contrast, the existence of tax inspections increases the probability of GVC participation and deepening. Increased tax inspection may be a sign of institutional quality and procedural rigour, so it should not be surprising that it helps firms to participate in GVCs. The opposite can be expected from practices of competitors in the informal sector, which are an obstacle to firms' operations (Bacchetta et al., 2009). We find that they significantly harm participation and deepening in GVCs. According to the World Bank (2019) report, a major challenge for emerging economies is the existence of persistent informality in employment. The report highlights that in Sub-Saharan Africa around 75% of employment between 2006 and 2016 was informal.

In addition, having a security system in place always has a significant and positive impact. Crime is a major obstacle in Africa, preventing firms from doing business properly, generating large losses and becoming a serious constraint to new investments

and business performance (United Nations: Office of Drugs and Crime, 2005; Bah and Fang, 2015).

Finally, the results of the two country-level variables in the regressions indicate that higher import costs or time to export work against firms' participation and deepening in GVCs. In other words, trade procedures are essential to smooth and facilitate the functioning of chains (OECD and WTO, 2015). These results are consistent with those found in Slany (2019) for regional value chains (RVCs) in a study using aggregate country-level data for 37 African countries from the UNCTAD-Eora database. The author finds that higher trade costs can hinder countries' participation in RVCs. In addition, she notes that variables affecting RVCs can also affect integration into GVCs.

*THE IMPACT OF PARTICIPATION IN GVCs ON PERFORMANCE MEASURES*

Table 3.3 presents the results of estimating the models in (3.3) and (3.4) by the instrumental variables method. Starting with the endogeneity tests, the bottom half of Table 3.3 shows the instrument-related tests for each GVC indicator selected as a regressor in the firm performance equations. First, we reject exogeneity of the GVC indicators. Second, we reject that instruments have no explanatory power over the GVC indicator they are instrumenting. Finally, we do not reject the null hypothesis of joint exclusion of IVs in the firm performance equations. This means that they affect performance variables only through their effects on GVC indicators. These results reveal that there was an endogeneity problem in the performance equations and that our instruments are valid.[73]

[73] For more details on the statistical significance of each individual instrument when instrumenting a GVC indicator in a specific performance equation of interest (R&D, product innovation, process innovation, labour productivity, wages per worker or number of workers) see Tables S1-S6 of the supplementary material.

Table 3.3. Estimated marginal effects –The impact of participation in GVCs on performance measures (IV strategy instrumenting potentially endogenous GVC indicators).

| | (1) R&D DECISION | (2) NEW PRODUCT | (3) NEW PROCESS | (4) LABOUR PRODUCTIVITY | (5) WAGES | (6) WORKERS |
|---|---|---|---|---|---|---|
| TWO WAY TRADER[a,aa,aaa] | 0.153*** (0.041) | 0.278*** (0.034) | 0.208*** (0.038) | 0.197 (0.367) | 4.134*** (1.053) | 2.556*** (0.233) |
| GVC FOREIGN[b,bb,bbb] | 0.222*** (0.073) | 0.316*** (0.078) | 0.202*** (0.067) | 0.606† (0.381) | 0.543*** (0.202) | 3.276*** (0.265) |
| GVC CERTIFICATE[c,cc,ccc] | 0.291*** (0.085) | 0.380*** (0.047) | 0.259*** (0.095) | 5.047*** (1.310) | 4.334*** (0.980) | 0.930*** (0.210) |
| GVC ALL[d,dd,ddd] | 0.240*** (0.091) | 0.357*** (0.071) | 0.325*** (0.118) | 5.623*** (1.111) | 4.829*** (0.854) | 3.442*** (0.309) |
| FVA[e,ee,eee] | 0.0001*** (0.00003) | 0.0001*** (0.00003) | -0.133*** (0.035) | -0.0002*** (0.00003) | 0.0003*** (0.0001) | 0.002*** (0.00001) |
| IVA[f,ff,fff] | 0.100*** (0.017) | 0.264*** (0.070) | 0.135*** (0.033) | 0.942** (0.406) | 0.103 (0.196) | 2.839*** (0.379) |
| Observations | 2,519-5,610 | 3,169-7,218 | 3,055-7,191 | 4,255-10,378 | 4,102-10,047 | 4,568-11,060 |
| [a] Correlation dependent variable and GVC indicator errors | -0.119* (0.072) | -0.345*** (0.068) | -0.196*** (0.055) | 0.063*** (0.016) | -1.134*** (0.358) | -0.463*** (0.116) |
| [aa] Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 433.81 0.0000 | 364.25 0.0000 | 426.77 0.0000 | 19.99 0.0000 | 22.54 0.0010 | 105.63 0.0000 |
| [aaa] Chi2 test and p-value of joint exclusion of IVs in the dependent variable equation | 2.24 0.5244 | 1.83 0.8721 | 3.65 0.4555 | 0.00 0.9687 | 5.15 0.3976 | 1.98 0.3721 |
| [b] Correlation dependent variable and GVC indicator errors | -0.243*** (0.090) | -0.473*** (0.174) | -0.249** (0.107) | 0.044*** (0.013) | 0.007 (0.022) | -0.589*** (0.119) |

| | | | | | | |
|---|---|---|---|---|---|---|
| [bb] Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 198.17<br>0.0000 | 234.95<br>0.0000 | 176.70<br>0.0000 | 115.44<br>0.0000 | 331.27<br>0.0000 | 113.59<br>0.0000 |
| [bbb] Chi2 test and p-value of joint exclusion of IVs in the dependent variable equation | 1.59<br>0.2066 | 0.49<br>0.4855 | 3.09<br>0.2130 | 1.21<br>0.5466 | 0.74<br>0.9467 | 1.78<br>0.1823 |
| [c] Correlation dependent variable and GVC indicator errors | -0.215*<br>(0.121) | -0.527***<br>(0.119) | -0.204†<br>(0.128) | -0.929***<br>(0.290) | -1.073***<br>(0.276) | -0.008<br>(0.008) |
| [cc] Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 131.94<br>0.0000 | 154.46<br>0.0000 | 136.40<br>0.0000 | 17.08<br>0.0002 | 29.19<br>0.0000 | 137.38<br>0.0000 |
| [ccc] Chi2 test and p-value of joint exclusion of IVs in the dependent variable equation | 1.62<br>0.2024 | 0.00<br>0.9658 | 0.43<br>0.5143 | 1.00<br>0.3161 | 3.48<br>0.4807 | 2.70<br>0.2591 |
| [d] Correlation dependent variable and GVC indicator errors | -0.204*<br>(0.120) | -0.601***<br>(0.183) | -0.378*<br>(0.204) | -1.050***<br>(0.257) | -1.394***<br>(0.218) | -0.318***<br>(0.105) |
| [dd] Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 80.57<br>0.0000 | 104.62<br>0.0000 | 79.76<br>0.0000 | 21.57<br>0.0000 | 74.51<br>0.0000 | 72.64<br>0.0000 |
| [ddd] Chi2 test and p-value of joint exclusion of IVs in the dependent variable equation | 3.48<br>0.1759 | 1.31<br>0.2520 | 0.41<br>0.8154 | 1.91<br>0.1673 | 5.66<br>0.3412 | 0.01<br>0.9288 |

| | | | | | | |
|---|---|---|---|---|---|---|
| [e] Correlation dependent variable and GVC indicator errors | 0.210***<br>(0.033) | 0.170***<br>(0.021) | 0.250***<br>(0.037) | 0.067***<br>(0.018) | 0.054***<br>(0.021) | 0.072***<br>(0.011) |
| [ee] Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 8.02<br>0.0181 | 7.36<br>0.0252 | 11.11<br>0.0254 | 38.23<br>0.0000 | 12.19<br>0.0068 | 37.35<br>0.0000 |
| [eee] Chi2 test and p-value of joint exclusion of IVs in the dependent variable equation | 0.73<br>0.3917 | 0.11<br>0.7412 | 0.54<br>0.9095 | 2.17<br>0.8249 | 0.67<br>0.7144 | 0.31<br>0.8551 |
| [f] Correlation dependent variable and GVC indicator errors | 0.196<br>(0.164) | -0.246***<br>(0.084) | -0.01<br>(0.109 | 0.003<br>(0.018) | 0.063***<br>(0.013) | -0.511***<br>(0.110) |
| [ff] Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 9.40<br>0.0091 | 36.90<br>0.0000 | 20.24<br>0.0000 | 21.68<br>0.0000 | 51.79<br>0.0000 | 8.02<br>0.0182 |
| [fff] Chi2 test and p-value of joint exclusion of IVs in the dependent variable equation | 0.98<br>0.3228 | 1.24<br>0.5368 | 1.60<br>0.2055 | 0.76<br>0.3839 | 1.21<br>0.8756 | 0.24<br>0.6208 |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1, † slightly above 0.1. (iii) All regressions control for country, sector and year dummies as well as for firm size and age. (iv) For the equations instrumenting the potentially endogenous GVC indicator, explanatory variables are the control variables in equations (3) and (4), sector, country and year dummies, and the corresponding external instruments. The pool of potential external instruments comes from the business environment variables in equations (1) and (2). Among this pool, IVs were selected in each case on the basis of the required conditions for IVs validity: 1) have explanatory power over the instrumented GVC indicator; and, 2) not having a direct effect as a regressor in the outcome (performance) equation of interest.

The results in Table 3.3 show that Sub-Saharan countries can reap benefits from participation in GVCs, as participating firms innovate more, are more productive, pay higher wages and turn out to be larger. Among the innovation-related variables, the largest marginal effects are found for product innovation, which may indicate the need for product upgrading. Moreover, in most cases, the GVC all participation indicator (the strictest, requiring the firm to be a two-way trader with foreign capital participation and an international certificate) has the greatest effect. However, the effect of GVC certificate is slightly higher on the R&D decision and product innovation.

There are only a few exceptions to these general results. One is that two-way trader, if not combined with foreign participation or international certification, does not have a statistically significant effect on productivity. Similarly, IVA has no significant effect on wages. As for FVA, what is relevant for process innovation and labour productivity is participation in GVCs through backward (downstream) integration and not the intensity. Its intensification at some point weakens the incentives for efficiency through process innovation. This is also likely to have a negative effect on labour productivity.[74] This possibly indicates the existence of a threshold beyond which an increase in foreign value added in firms' exports discourages process innovation and negatively affects productivity.

[74] Recall that the two-way trader dummy variable in Table 3.3 takes the value 1 when the FVA variable is positive and zero when the FVA variable is 0. Therefore, the two-way trader dummy can be interpreted as the dichotomised version of FVA. This two-way trader dummy variable can appear in combination with foreign capital participation or international certification. While these dummy versions of FVA tend to positively affect process innovation and productivity, their corresponding intensive margin measure has a negative and significant coefficient.

## 3.6. Robustness checks

We perform three robustness checks of our results in the chapter. Two for the first objective of the chapter, i.e. the determinants of firms' participation in GVCs, and one for the second, i.e. the effects of participation on firms' performance variables. First, Table A3.3 in Appendix 3 shows the results of Table 3.2.2 when the intensive margin measures of GVC participation “FVA” and “IVA” relax the original proportionality assumptions. FVA was calculated assuming that the proportion of foreign inputs is the same in exports as in domestic sales, while it is now calculated assuming that for exporters the share of foreign inputs in domestic sales is the same as the average of non-exporting firms in the same sector-country-year. Moreover, IVA was calculated assuming that the proportion of domestic value added is the same in exports as in domestic sales, while it is now calculated assuming that for exporters the share of domestic value added in domestic sales is the same as the average of non-exporting firms in the same sector-country-year. The results for the new dependent variables, FVA and IVA, broadly mimic those in Table 3.2.2. This confirms that our original proportionality assumptions, also present in aggregate measures at country or sector-country level in international databases such as UNCTAD-Eora, do not lead to misleading results, as anticipated by Ahmad (2013).

Second, we repeat our analysis of the determinants of GVC participation by replacing firm-level regressors from WBES with similar country-level regressors from the World Bank's Doing Business. Table A3.4 in Appendix 3 shows the results of these regressions. As these regressions also include country and year dummies, it is not surprising that regressors with little within-country time variation, such as access to electricity (as an indicator of the level of infrastructure), level of tertiary education (as an indicator of skills) or government effectiveness (as an indicator of the quality of

institutions), are not significant.[75] In contrast, when others are significant, they have the expected signs. This is the case of a country's better position in the ICT Development Index (IDI), which is a proxy for infrastructure that positively affects GVC participation, or lower access to bank financing, higher crime rates (proxy for security) and a lower position in the Logistics Performance Index (proxy for trade procedures), all of which have a negative sign.[76]

Finally, Table A3.5 in Appendix 3 shows the results of using the propensity score matching method instead of the instrumental variables approach to assess the effects of GVC participation on firm performance measures. The results of the balancing tests can be found in Tables S7-S11 of the supplementary material.[77] There it is confirmed that, after matching, the covariates have statistically the same mean in the two groups and that, therefore, the matching procedure has been able to balance the treated and untreated groups, creating a homogeneous group with common characteristics. In addition, Figure S1 in the supplementary material shows the density plots of the GVC propensity scores

[75] Electricity access is measured as the percentage of population with access to electricity. The level of tertiary education is calculated as the gross percentage of school enrolment on tertiary education. Government effectiveness is measured as the country's position in the government effectiveness ranking from the World Bank's Worldwide Governance Indicators. Government effectiveness reflects perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. It ranges from 0 (lowest) to 100 (highest) rank.

[76] The IDI variable measures a country's position in the IDI ranking showing advances in information and communication technology, where higher values mean a better position in the ranking. Access to bank financing measures the percentage of firms not using banks to finance working capital. Crime rates are measured as losses due to theft and vandalism expressed as a percentage of annual sales of affected firms. The Logistics Performance Index measures performance along the country's entire logistics supply chain, with higher values indicating worse performance.

[77] Table S11 reports the test on overall significance of covariates in the probit models for propensity score matching after the matching.

before and after matching for the treated and untreated groups. The similarity between the groups after matching further confirms matching quality.

The results in Table A3.5 are qualitatively consistent with those in Table 3.3 above, as most of the GVC participation indicators have positive and significant effects on firms' innovation and employment measures. However, there are quantitative differences. Thus, the effects of GVC participation with propensity score matching methods are generally smaller, except for labour productivity with indicators other than GVC certificate and GVC all. The reason may be that in observational studies the two methods for testing a hypothesised causal relationship, design-based methods such as propensity score matching and instrument-based methods such as instrumental variables, target different populations, which is relevant for interpretation of results. Thus, IV analysis focuses on the local average treatment effect (LATE), which is the treatment effect for those whose treatment status is affected (changed) by the instruments. In our case, it is the effect on our performance measures for those firms whose GVC participation is affected by the instruments. In contrast, propensity score matching provides the average treatment effect among the treated (ATT), i.e. the difference between the average performance measures observed for GVC participants and those they would have experienced had they not participated. The target population is the treated firms. This makes the estimates resulting from instrumental variables analysis not directly comparable to the results obtained with propensity score matching methods. For this reason, the best path to causal inference is to recognise the complementarity of the two approaches.

## 3.7. Conclusions

This chapter analyses GVCs in Sub-Saharan Africa using firm-level data from WBES. It answers two questions. First, what business environment factors determine firms' participation in GVCs. Second, what are the effects of participation on different

measures of firm performance. Regarding the first question, we find that good infrastructure, quality of institutions and security to prevent crime favour participation. In contrast, difficult access to finance, the existence of an informal sector or high trade costs discourage participation. Related to this, while there are several multi-country and regional aid for trade projects in Africa aimed at alleviating barriers to trade and infrastructure (OECD, WTO, 2015), new complementary policies targeting the remaining barriers would be needed.

A result to reflect on is that obtained for workers´ skill intensity, with a negative effect on the likelihood of participating in GVCs. So far, Sub-Saharan countries have the comparative advantage of being endowed with abundant low-cost unskilled labour, which has been attractive for labour-intensive manufacturing activities. However, as Rodrik (2018) highlights, GVCs are increasingly intensive in new technologies, which may pose a threat to these countries. The lack of skills required to handle these technologies may diminish their comparative advantage, as several authors highlight the importance of skilled labour (Hollweg, 2019) or even automation (Stapleton, 2019) in GVCs. Policy makers should pay attention to this risk.

Regarding the second question, we find that Sub-Saharan African firms participating in GVCs enjoy superior innovation performance (both in terms of product upgrading and efficiency gains), higher productivity, pay higher wages and generate more employment. This suggests that their participation can help them to grow, develop and play an active role in the international arena. However, they still have a long way to go.

An interesting exception to these general results seems to suggest that excessive backward integration, i.e. excessive imported input content in exports (as measured by FVA), may negatively affect incentives for process innovation and productivity of manufacturing firms in Sub-Saharan Africa. More research is needed to understand why

this may occur, but perhaps an excess of foreign content in exports implies excessive technological substitution that discourages process innovation and negatively affects productivity. Importing intermediates, which may incorporate technology, may at some point substitute for internal knowledge, negatively affect absorptive capacity and hinder firms' incentives for process innovation. The fact that there is a negative effect on productivity may reinforce the idea of a deterioration of firms' absorptive capacity for imported technology beyond a threshold.

Finally, although this study provides relevant insights at the firm level, we acknowledge the limitation of the pooled dataset nature of WBES. As the issue of endogeneity may arise with this type of data, in this chapter we implement IVs strategies consisting of estimating the joint likelihood function of each dependent variable and the potentially endogenous regressors (limited information maximum likelihood - LIML) or implementing a control function approach (Rivers and Vuong, 1988), as suggested by Wooldridge (2015). In addition, we also test the robustness of our results on the effects of GVC participation by alternatively using a propensity score methodology. In any case, it is a challenge for future research in this area to have rich firm-level panel surveys covering Sub-Saharan countries in a comparable manner.

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# APPENDIX 3

Table A3.1. Definitions - Business environment variables (most at firm level)

| VARIABLE | SOURCE | DEFINITION |
|---|---|---|
| **OUTAGE (INFRASTRUCTURE)** | WBES | Dummy equal to one if the establishment experienced power outages over last fiscal year, and zero otherwise. |
| **GENERATOR (INFRASTRUCTURE)** | WBES | Dummy equal to one if the establishment owned or shared a generator last fiscal year, and zero otherwise. |
| **WEB (INFRASTRUCTURE)** | WBES | Dummy equal to one if the establishment has its own website at the present time, and zero otherwise. |
| **SKILLED INTENSITY (LABOUR)** | WBES | Ratio of skilled workers/total number of workers (multiplied by 100). |
| **AVERAGE OBST LABOUR (LABOUR)** | WBES | Labour regulation as the biggest obstacle faced by establishments in the same country-sector-year. Measured subtracting the individual firm's own response to the country-sector-year average. |
| **OBST FINANCE (FINANCE)** | WBES | Dummy equal to one if the biggest obstacle faced by the establishment is access to finance, and zero otherwise. |
| **TAX INSPECTION (TAXATION)** | WBES | Dummy equal to one if the establishment was visited or inspected by tax officials or required to meet with them over last year, and zero otherwise. |
| **OBST TAX (TAXATION)** | WBES | Dummy equal to one if the biggest obstacle faced by the establishment are tax rates, and zero otherwise. |
| **INFORMALITY** | WBES | Dummy equal to one if practices of competitors in the informal sector are a very severe obstacle to the current operations of the establishment, and zero otherwise. |
| **SECURITY** | WBES | Dummy equal to one if the establishment payed for security last fiscal year, for example equipment, personnel, or professional security services including internet security, and zero otherwise. |
| **IMPORT COST (TRADE PROCEDURES)** | DB | Trading across Borders - Cost to import (US$ per container deflated). Multiplied by 1000. |
| **EXPORT DAYS (TRADE PROCEDURES)** | DB | Trading across Borders - Time to export (days) |

Note: WBES corresponds to World Bank Enterprise Survey and DB to World Bank's Doing Business (firm-level and country-year data, respectively).

Table A3.2. Definitions – Performance variables: related to innovation and employment (at firm level)

| VARIABLE | SOURCE | DEFINITION |
|---|---|---|
| **R&D DECISION** | WBES | Dummy equal to one if the establishment spent on research and development activities, either in-house or contracted with other companies (excluding market research surveys) during last fiscal year, and zero otherwise. |
| **NEW PRODUCT** | WBES | Dummy equal to one if the establishment introduced new or improved products or services during the last three years, and zero otherwise |
| **NEW PROCESS** | WBES | Dummy equal to one if the establishment introduced any new or improved process during the last three years, and zero otherwise |
| **LABOUR PRODUCTIVITY** | WBES | Ratio of labour productivity/country-sector-year average of labour productivity. Labour productivity calculated as sales/workers. |
| **WAGES** | WBES | Ratio of wages/country-sector-year average of wages. Wages calculated as labour cost/workers. |
| **WORKERS** | WBES | Ratio of number of workers/country-sector-year average of workers |

Note: WBES corresponds to World Bank Enterprise Survey

Table A3.3. Estimated marginal effects –Business environment factors determining participation in GVCs (relaxing the proportionality assumptions in the calculation of dependent variables new FVA and new IVA).

| VARIABLES | (1)<br>FVA | (2)<br>IVA |
|---|---|---|
| **Outage** | 0.028<br>(0.082) | -0.110<br>(0.149) |
| **Generator** | 0.221***<br>(0.056) | 0.213***<br>(0.075) |
| **Web** | 0.356***<br>(0.063) | 0.451***<br>(0.156) |
| **Skilled intensity** | -0.003***<br>(0.001) | -0.002<br>(0.002) |
| **Average obst labour** | -3.446***<br>(1.276) | 1.973<br>(3.739) |
| **Obst finance** | -0.101†<br>(0.069) | -0.234**<br>(0.104) |
| **Tax inspection** | 0.089†<br>(0.058) | 0.193*<br>(0.098) |
| **Obst tax** | -0.084†<br>(0.055) | -0.209*<br>(0.108) |
| **Informality** | -0.165***<br>(0.059) | -0.280**<br>(0.115) |
| **Security** | 0.207***<br>(0.068) | 0.033<br>(0.091) |
| **Import cost** | -0.023<br>(0.017) | -0.234**<br>(0.114) |
| **Export days** | -0.062***<br>(0.005) | -0.107***<br>(0.024) |
| **Size** | 0.583***<br>(0.064) | 0.583***<br>(0.099) |
| **Log age** | 0.078**<br>(0.038) | 0.069<br>(0.070) |
| **Constant** | 1.628***<br>(0.380) | 4.925***<br>(1.513) |
| Observations | 8,561 | 3,573 |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1, † slightly above 0.1. (iii) All regressions control for country, sector and year dummies as well as for firm size and age. (iv) FVA was calculated assuming that the proportion of inputs of foreign origin is spread equally to exports and to domestic sales, while *new* FVA has been calculated assuming instead that for exporters the proportion of foreign inputs in domestic sales is the same as the average one for non-exporting firms in the same sector-country-year. (v) IVA was calculated assuming that the proportion of Domestic Value Added is spread equally to exports and to domestic sales, while *new* IVA has been calculated assuming instead that for exporters the proportion of Domestic Value Added in domestic sales is the same as the average one for non-exporting firms in the same sector-country-year. (vi) The same estimation procedure has been used as for the main text results in Table 3.2.2.

Table A3.4. Estimated marginal effects –Business environment factors determining participation in GVCs (results with country-level regressors)

| | (1) TWO-WAY TRADER | (2) GVC FOREIGN | (3) GVC CERTIFICATE | (4) GVC ALL |
|---|---|---|---|---|
| **Electricity access** | -0.001 | 0.002 | -0.001 | -0.001 |
| | (0.003) | (0.002) | (0.002) | (0.001) |
| **IDI** | 0.005*** | 0.003*** | -0.001 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| **Tertiary education** | -0.002 | -0.014 | 0.006 | 0.002 |
| | (0.016) | (0.011) | (0.012) | (0.005) |
| **Bank use** | 0.006 | 0.002 | 0.002 | -0.002† |
| | (0.004) | (0.003) | (0.003) | (0.001) |
| **Crime** | -0.032** | -0.001 | -0.003 | 0.000 |
| | (0.014) | (0.009) | (0.011) | (0.005) |
| **Government effectiveness** | -0.001 | 0.000 | -0.000 | -0.001 |
| | (0.002) | (0.001) | (0.001) | (0.001) |
| **LPI** | -0.044 | -0.162** | -0.020 | -0.035* |
| | (0.092) | (0.064) | (0.073) | (0.021) |
| **size** | 0.199*** | 0.090*** | 0.091*** | 0.044*** |
| | (0.009) | (0.006) | (0.006) | (0.004) |
| **Log age** | 0.034*** | 0.003 | 0.029*** | 0.009*** |
| | (0.006) | (0.004) | (0.004) | (0.003) |
| **Constant** | 0.987 | -4.290 | -6.158 | -1.390 |
| | (3.176) | (4.660) | (5.033) | (4.030) |
| Observations | 7,332 | 7,260 | 7,142 | 6,960 |

Notes: (i) Robust standard errors in parentheses. (ii)*** p<0.01, ** p<0.05, * p<0.1; † slightly above 0.1. (iii) All regressions control for country, sector and year dummies.

Table A3.5. Estimated marginal effects (ATT) –The impact of participation in GVCs on performance measures (propensity score matching method).

| | (1) R&D DECISION | (2) NEW PRODUCT | (3) NEW PROCESS | (4) LABOUR PRODUCTIVITY | (5) WAGES | (6) WORKERS |
|---|---|---|---|---|---|---|
| TWO WAY | 0.101*** | 0.044** | 0.063** | 0.787*** | 0.322*** | 0.405*** |
| TRADER | (0.021) | (0.022) | (0.028) | (0.149) | (0.084) | (0.144) |
| GVC | 0.034 | -0.035 | -0.020 | 1.015*** | 0.685*** | 0.256 |
| FOREIGN | (0.044) | (0.032) | (0.0349 | (0.229) | (0.170) | (0.250) |
| GVC | 0.109*** | 0.064† | 0.114*** | 0.936*** | 0.496*** | 1.180*** |
| CERTIFICATE | (0.039) | (0.043) | (0.045) | (0.217) | (0.164) | (0.229) |
| GVC ALL | 0.139** | -0.071 | 0.058 | 1.121*** | 0.795*** | 0.983*** |
| | (0.068) | (0.055) | (0.060) | (0.352) | (0.224) | (0.481) |
| Observations | 4,455-4,656 | 5,133-5,316 | 5,132-5,288 | 7,981-8,173 | 7,741-7,921 | 8,534-8,749 |

Notes: (i) *** p<0.01, ** p<0.05, * p<0.1, † slightly above 0.1. (ii) Bootstrap standard errors.

## Supplementary material

Table S1. Estimated marginal effects – First-step IVs for future estimation of "R&D" dependent variable.

| | (1) TWO-WAY TRADER | (2) GVC FOREIGN | (3) GVC CERTIFICATE | (4) GVC ALL | (5) FVA | (6) IVA |
|---|---|---|---|---|---|---|
| **Web** | 0.128*** | 0.063*** | 0.078*** | 0.035*** | | |
| | (0.012) | (0.008) | (0.007) | (0.010) | | |
| **Skilled intensity** | -0.001*** | | | | | |
| | (0.000) | | | | | |
| **Average obst labour** | | | | | -0.276** | |
| | | | | | (0.118) | |
| **Obst finance** | -0.039*** | -0.036*** | | -0.012*** | | -0.041*** |
| | (0.011) | (0.005) | | (0.004) | | (0.014) |
| **Tax inspection** | 0.031*** | | | | | |
| | (0.011) | | | | | |
| **Informality** | | | -0.016*** | -0.008** | -0.026*** | -0.038*** |
| | | | (0.005) | (0.004) | (0.010) | (0.014) |
| **Export days** | | | | | | |
| Observations | 9,779 | 10,320 | 10,763 | 10,010 | 10,166 | 4,275 |
| Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 433.81<br>0.0000 | 198.17<br>0.0000 | 131.94<br>0.0000 | 80.57<br>0.0000 | 8.02<br>0.0181 | 9.40<br>0.0091 |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1 (iii) All regressions control for country, sector and year dummies as well as for firm size and age.

Table S2. Estimated marginal effects – First-step IVs for future estimation of "New product" dependent variable.

| | (1) TWO-WAY TRADER | (2) GVC FOREIGN | (3) GVC CERTIFICATE | (4) GVC ALL | (5) FVA | (6) IVA |
|---|---|---|---|---|---|---|
| **Web** | 0.138*** | 0.068*** | 0.066*** | 0.034*** | | 0.101*** |
| | (0.014) | (0.008) | (0.005) | (0.003) | | (0.024) |
| **Skilled intensity** | -0.001*** | | | | | |
| | (0.000) | | | | | |
| **Average obst labour** | -0.378** | | | | -0.248** | |
| | (0.171) | | | | (0.118) | |
| **Obst finance** | -0.045*** | -0.037*** | | -0.017*** | | -0.036** |
| | (0.011) | (0.005) | | (0.006) | | (0.015) |
| **Obst tax** | -0.022** | | | | | |
| | (0.009) | | | | | |
| **Informality** | -0.039*** | | -0.018*** | | -0.025** | -0.033** |
| | (0.010) | | (0.006) | | (0.010) | (0.014) |
| Observations | 9,806 | 10,320 | 10,758 | 10,010 | 10,166 | 4,265 |
| Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 364.25<br>0.0000 | 234.95<br>0.0000 | 154.46<br>0.0000 | 104.62<br>0.0000 | 7.36<br>0.0252 | 36.90<br>0.0000 |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1 (iii) All regressions control for country, sector and year dummies as well as for firm size and age.

Table S3. Estimated marginal effects – First-step IVs for future estimation of "New process" dependent variable.

| | (1) TWO-WAY TRADER | (2) GVC FOREIGN | (3) GVC CERTIFICATE | (4) GVC ALL | (5) FVA | (6) IVA |
|---|---|---|---|---|---|---|
| **Web** | 0.134*** | 0.055*** | 0.078*** | 0.036*** | | 0.490*** |
| | (0.013) | (0.018) | (0.008) | (0.014) | | (0.116) |
| **Skilled intensity** | -0.001*** | -0.000* | | | | |
| | (0.000) | (0.000) | | | | |
| **Average obst labour** | | | | | -0.294** | |
| | | | | | (0.118) | |
| **Obst finance** | -0.043*** | -0.041*** | | -0.012*** | -0.039*** | |
| | (0.011) | (0.014) | | (0.005) | (0.010) | |
| **Obst tax** | -0.020** | | | | -0.019** | |
| | (0.010) | | | | (0.009) | |
| **Informality** | -0.037*** | | -0.016*** | -0.008** | -0.028** | -0.210** |
| | (0.010) | | (0.005) | (0.004) | (0.012) | (0.103) |
| Observations | 9,806 | 9,730 | 10,763 | 10,010 | 10,166 | 4,588 |
| Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 426.77<br>0.0000 | 176.70<br>0.0000 | 136.40<br>0.0000 | 79.76<br>0.0000 | 11.11<br>0.0254 | 20.24<br>0.0000 |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1 (iii) All regressions control for country, sector and year dummies as well as for firm size and age.

Table S4. Estimated marginal effects – First-step IVs for future estimation of "Labour productivity" dependent variable.

| | (1) TWO-WAY TRADER | (2) GVC FOREIGN | (3) GVC CERTIFICATE | (4) GVC ALL | (5) FVA | (6) IVA |
|---|---|---|---|---|---|---|
| **Web** | | 0.068*** | 0.091*** | 0.045*** | | 0.487*** |
| | | (0.009) | (0.008) | (0.010) | | (0.110) |
| **Skilled intensity** | -0.0005*** | -0.0003** | | | -0.002*** | |
| | (0.0002) | (0.0001) | | | (0.0007) | |
| **Average obst labour** | | | | | -1.156** | |
| | | | | | (0.573) | |
| **Obst finance** | | | | | | |
| **Tax inspection** | | | 0.020*** | | | |
| | | | (0.005) | | | |
| **Obst tax** | | | | | -0.067* | |
| | | | | | (0.037) | |
| **Informality** | -0.041*** | | | -0.011† | -0.122** | -0.210** |
| | (0.011) | | | (0.007) | (0.050) | (0.105) |
| **Import cost** | | -0.020*** | | | -0.057*** | |
| | | (0.006) | | | (0.015) | |
| **Export days** | | | | | -0.044*** | |
| | | | | | (0.007) | |
| Observations | 9,822 | 9,417 | 10,729 | 10,635 | 8,668 | 4,586 |
| Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 19.99<br>0.0000 | 115.44<br>0.0000 | 17.08<br>0.0002 | 21.57<br>0.0000 | 38.23<br>0.0000 | 21.68<br>0.0000 |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1 (iii) All regressions control for country, sector and year dummies as well as for firm size and age.

Table S5. Estimated marginal effects – First-step IVs for future estimation of "Wages" dependent variable.

| | (1) TWO-WAY TRADER | (2) GVC FOREIGN | (3) GVC CERTIFICATE | (4) GVC ALL | (5) FVA | (6) IVA |
|---|---|---|---|---|---|---|
| **Outage** | | | | -0.026** | | |
| | | | | (0.010) | | |
| **Generator** | 0.044*** | 0.036*** | 0.042*** | 0.026*** | | |
| | (0.008) | (0.008) | (0.007) | (0.007) | | |
| **Web** | 0.101*** | 0.059*** | 0.072*** | 0.054*** | | |
| | (0.020) | (0.007) | (0.005) | (0.010) | | |
| **Skilled intensity** | -0.0004*** | -0.0003** | | | | -0.003** |
| | (0.0001) | (0.0001) | | | | (0.001) |
| **Average obst labour** | | | -0.191** | | -0.992* | |
| | | | (0.081) | | (0.542) | |
| **Obst finance** | -0.038*** | -0.035*** | | -0.022*** | | |
| | (0.007) | (0.005) | | (0.008) | | |
| **Tax inspection** | | | 0.016* | 0.012* | 0.141*** | 0.155* |
| | | | (0.008) | (0.007) | (0.049) | (0.092) |
| **Obst tax** | -0.016† | | | | | |
| | (0.010) | | | | | |
| **Informality** | | | -0.023*** | -0.019*** | -0.106** | -0.261** |
| | | | (0.008) | (0.006) | (0.049) | (0.105) |
| **Security** | 0.037** | | | | | |
| | (0.017) | | | | | |
| **Import cost** | | -0.016*** | | | | -0.175*** |
| | | (0.003) | | | | (0.066) |
| **Export days** | | | | | | -0.100*** |
| | | | | | | (0.018) |
| Observations | 8,831 | 8,768 | 10,647 | 9,689 | 10,793 | 3,921 |
| Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 22.54<br>0.0010 | 331.27<br>0.0000 | 29.19<br>0.0000 | 74.51<br>0.0000 | 12.19<br>0.0068 | 51.79<br>0.0000 |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1 (iii) All regressions control for country, sector and year dummies as well as for firm size and age.

Table S6. Estimated marginal effects – First-step IVs for future estimation of "Workers" dependent variable.

| | (1) TWO-WAY TRADER | (2) GVC FOREIGN | (3) GVC CERTIFICATE | (4) GVC ALL | (5) FVA | (6) IVA |
|---|---|---|---|---|---|---|
| **Outage** | | | | -0.008** | | |
| | | | | (0.004) | | |
| **Web** | 0.134*** | 0.082*** | 0.060*** | 0.035*** | | |
| | (0.012) | (0.008) | (0.005) | (0.004) | | |
| **Average obst labour** | -0.368*** | | | | -1.240** | |
| | (0.120) | | | | (0.515) | |
| **Tax inspection** | | | 0.020*** | | | 0.161* |
| | | | (0.004) | | | (0.088) |
| **Informality** | -0.034*** | | -0.018*** | | | -0.192** |
| | (0.009) | | (0.006) | | | (0.078) |
| **Import cost** | | -0.020*** | | | -0.065*** | |
| | | (0.003) | | | (0.016) | |
| **Export days** | | | | | -0.040*** | |
| | | | | | (0.007) | |
| Observations | 10,405 | 9,921 | 10,672 | 10,565 | 9,112 | 4,568 |
| Chi2 test and p-value of joint non-significance of IVs in the equation instrumenting the GVC indicator | 105.63<br>0.0000 | 113.59<br>0.0000 | 137.38<br>0.0000 | 72.64<br>0.0000 | 37.35<br>0.0000 | 8.02<br>0.0182 |

Notes: (i) Robust standard errors in parentheses clustered by country and year. (ii)*** p<0.01, ** p<0.05, * p<0.1 (iii) All regressions control for country, sector and year dummies as well as for firm size and age.

Table S7. Matching method for GVC participation, using "Two-way trader". Balancing tests: Difference of means.

| | Mean | | t-test | |
|---|---|---|---|---|
| | Treated | Control | t-value | p-value |
| Outage | 0.875 | 0.896 | -1.72 | 0.086 |
| Generator | 0.692 | 0.698 | -0.37 | 0.713 |
| Web | 0.502 | 0.487 | 0.79 | 0.429 |
| Skilled intensity | 47.367 | 48.535 | -1.17 | 0.241 |
| Average obst labour | 0.010 | 0.009 | 0.69 | 0.489 |
| Obst finance | 0.129 | 0.114 | 1.21 | 0.225 |
| Tax inspection | 0.800 | 0.800 | -0.0 | 1.000 |
| Obst tax | 0.097 | 0.092 | 0.45 | 0.653 |
| Informality | 0.111 | 0.100 | 0.92 | 0.358 |
| Security | 0.809 | 0.822 | -0.87 | 0.382 |
| Import cost | 3.316 | 3.310 | 0.10 | 0.919 |
| Export days | 29.3 | 29.304 | -0.01 | 0.992 |

Note: The econometric model used for the matching procedure is based on equation (3.1), controlling for size, age and country dummies.

Table S8. Matching method for GVC participation, using "GVC foreign". Balancing tests: Difference of means.

| | Mean | | t-test | |
|---|---|---|---|---|
| | Treated | Control | t-value | p-value |
| Outage | 0.866 | 0.899 | -1.65 | 0.100 |
| Generator | 0.745 | 0.733 | 0.43 | 0.670 |
| Web | 0.578 | 0.560 | 0.57 | 0.571 |
| Skilled intensity | 44.905 | 45.158 | -0.16 | 0.873 |
| Average obst labour | 0.012 | 0.011 | 0.46 | 0.646 |
| Obst finance | 0.072 | 0.064 | 0.49 | 0.621 |
| Tax inspection | 0.825 | 0.831 | -0.25 | 0.804 |
| Obst tax | 0.105 | 0.101 | 0.20 | 0.838 |
| Informality | 0.115 | 0.107 | 0.40 | 0.691 |
| Security | 0.868 | 0.870 | -0.09 | 0.927 |
| Import cost | 3.406 | 3.392 | 0.13 | 0.896 |
| Export days | 29.942 | 29.916 | 0.04 | 0.968 |

Note: The econometric model used for the matching procedure is based on equation (3.1), controlling for size, age and country dummies.

Table S9. Matching method for GVC participation, using "GVC cert". Balancing tests: Difference of means.

| | Mean | | t-test | |
|---|---|---|---|---|
| | Treated | Control | t-value | p-value |
| Outage | 0.895 | 0.920 | -1.34 | 0.180 |
| Generator | 0.798 | 0.794 | 0.16 | 0.872 |
| Web | 0.712 | 0.700 | 0.43 | 0.670 |
| Skilled intensity | 47.846 | 47.28 | 0.35 | 0.726 |
| Average obst labour | 0.010 | 0.009 | 0.94 | 0.348 |
| Obst finance | 0.105 | 0.090 | 0.76 | 0.445 |
| Tax inspection | 0.855 | 0.851 | 0.18 | 0.855 |
| Obst tax | 0.107 | 0.103 | 0.21 | 0.833 |
| Informality | 0.101 | 0.078 | 1.25 | 0.212 |
| Security | 0.884 | 0.893 | -0.41 | 0.681 |
| Import cost | 3.343 | 3.328 | 0.13 | 0.894 |
| Export days | 30.004 | 30.004 | -0.06 | 0.950 |

Note: The econometric model used for the matching procedure is based on equation (3.1), controlling for size, age and country dummies.

Table S10. Matching method for GVC participation, using "GVC all". Balancing tests: Difference of means.

| | Mean | | t-test | |
|---|---|---|---|---|
| | Treated | Control | t-value | p-value |
| Outage | 0.838 | 0.883 | -1.31 | 0.192 |
| Generator | 0.797 | 0.792 | 0.12 | 0.901 |
| Web | 0.756 | 0.756 | -0.00 | 1.00 |
| Skilled intensity | 47.41 | 46.184 | 0.50 | 0.619 |
| Average obst labour | 0.010 | 0.009 | 0.75 | 0.453 |
| Obst finance | 0.061 | 0.046 | 0.67 | 0.502 |
| Tax inspection | 0.888 | 0.883 | 0.16 | 0.875 |
| Obst tax | 0.112 | 0.086 | 0.84 | 0.400 |
| Informality | 0.096 | 0.086 | 0.35 | 0.727 |
| Security | 0.904 | 0.914 | -0.35 | 0.727 |
| Import cost | 3.444 | 3.412 | 0.19 | 0.848 |
| Export days | 30.726 | 30.64 | 0.09 | 0.930 |

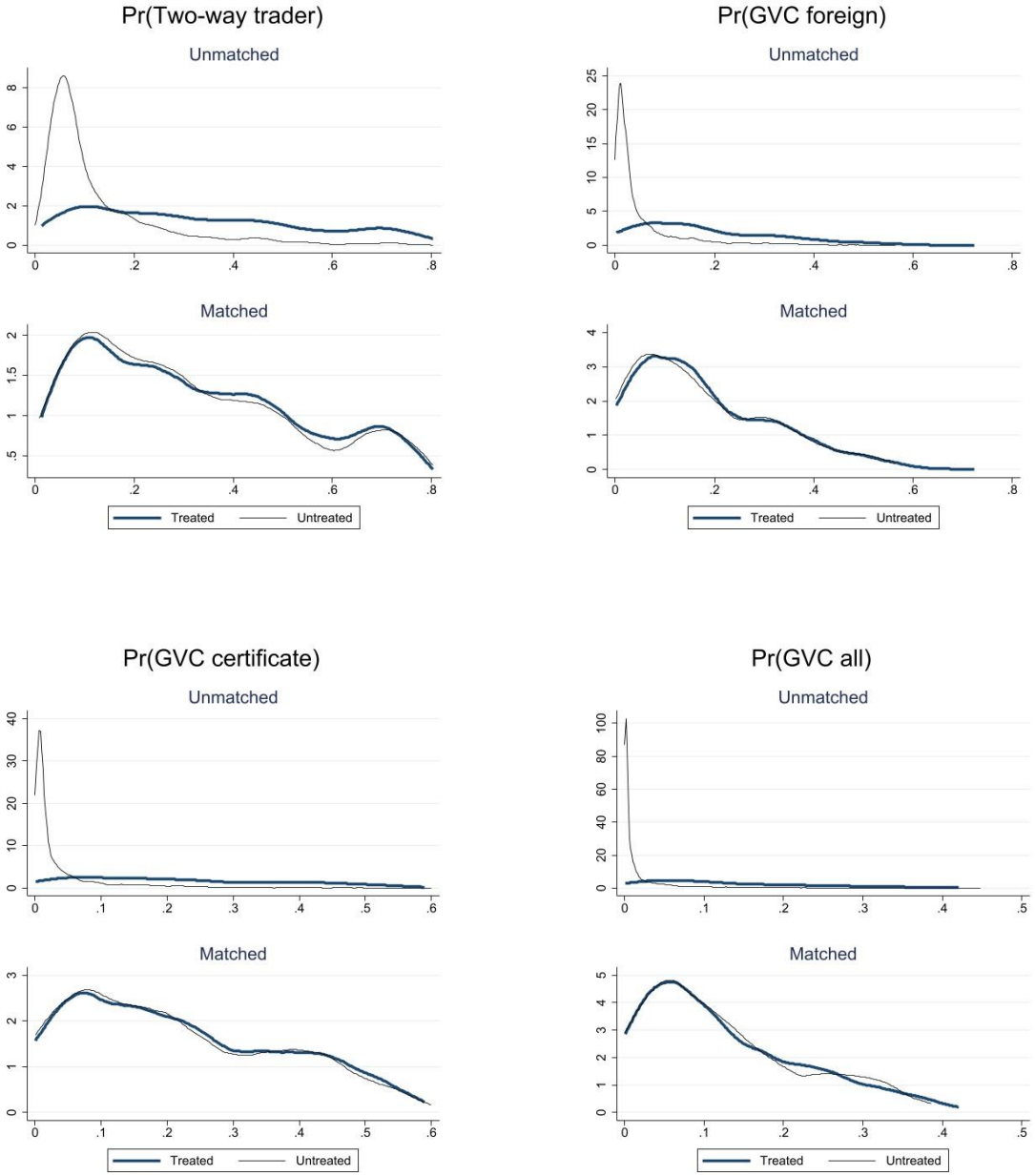
Note: The econometric model used for the matching procedure is based on equation (3.1), controlling for size, age and country dummies.

Table S11. Matching method for GVC participation. Overall measures of covariate balancing and number of observations after matching.

| | | Balancing tests | | Number of observations | | |
|---|---|---|---|---|---|---|
| Treatment | Control | LR Chi2 | p>Chi2 | Total | Treated | Control |
| Two-way trader | Non-two-way trader | 15.73 | 0.985 | 8,749 | 1,408 | 7,341 |
| GVC foreign | Non-GVC foreign | 8.51 | 1.000 | 8,676 | 514 | 8,162 |
| GVC certificate | Non-GVC certificate | 13.47 | 0.994 | 8,605 | 476 | 8,129 |
| GVC all | Non-GVC all | 5.61 | 1.000 | 8,534 | 197 | 8,337 |

Note: LR Chi2 reports the test on overall significance of covariates in the probit models for propensity score matching after the matching. Observations for total, treated and control samples are obtained after applying the matching procedure.

Figure S1. Density plots of the GVC variables before and after the matching.



# Chapter 4. Robots and firm reshoring

## 4.1. Introduction

New technologies such as robotics, one of the main automation technologies in manufacturing, may facilitate reshoring (Rodrik, 2018).[78] Reshoring can be broadly defined as a phenomenon that reverses offshoring, specifically referring to the return to the country of origin of previously offshored production of intermediate inputs or tasks for the production of intermediate inputs. If robotics reduce production costs in firms' home countries, it has the potential to reverse the offshoring of production tasks to other locations.

The phenomenon of reshoring and the subsequent debate are relatively recent. To date, research on this topic has mainly expected reshoring from developing to developed countries. This is in line with offshoring theories, which propose that developed countries offshore production to regions with lower income levels and, under specific conditions, subsequently reshore it (Rodrik, 2018; Krenz et al., 2021). In the models, the low-income regions of the world are treated as exogenous. This implies that wages in those countries do not adjust, and foreign countries do not invest in robotisation in response to the loss of their comparative advantage. One of the main contributions of our chapter is recognising the potential for reshoring from developed countries to other developed countries, driven by increased robotisation, which deviates from the assumptions made in existing models. In the real world, we recognise that there is a potential for reshoring from other developed countries. This is expected to occur when robot adoption leads to a reduction in the initial wage differential, which represents production costs, bringing the production costs in the

[78] In a broad sense, industrial robots are defined as 'automatically controlled, reprogrammable, multipurpose manipulators, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications' (ISO 8373, for details see https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en).

home country closer to those in other developed countries, albeit still higher than those in developing countries. This aspect can be particularly relevant for firms operating within the European Union (EU), where a significant proportion of intermediate inputs (such as materials, parts, components, or specific tasks involved in producing intermediate inputs) have previously been offshored to other EU countries or OECD countries (Organisation for Economic Co-operation and Development). This may be the case for Spanish manufacturing firms, as approximately 80% of their imports are sourced from the EU or the OECD.[79]

Another significant contribution of our chapter is acknowledging the real-world dynamics that differ from typical model assumptions. We recognise that countries to which production was previously offshored have the ability to react over time. In response to reshoring, these countries may choose to robotise their own production processes to regain competitiveness, particularly in the case of other developed countries. Alternatively, they may undergo a downward adjustment in wages, which is more likely for developing countries. It is important to note that this reaction effect, driven by robotisation in the home developed country, can influence the duration of reshoring, potentially leading to its eventual end. Finally, our work makes an additional noteworthy contribution by going beyond a unified index of reshoring. We adopt a more comprehensive approach by examining the specific mechanisms and factors involved in reshoring, such as the substitution of foreign sourcing with domestic suppliers or internal production within the firm. We find this step very interesting as it can have implications for the effects of robotisation, reshoring, and robotisation-induced reshoring on firms' employment. For instance, if reshoring involves replacing foreign suppliers with the

[79] This figure has been calculated using data from the representative sample of Spanish manufacturing used in this chapter.

firm's internal production, it can lead to an increase in the firm's employment. This is because the shift towards internal production requires additional workforce to handle the production tasks that were previously offshored.

In addition to the conceptual considerations discussed earlier, this chapter aims to address the lack of scientific evidence regarding the relationship between robotisation and reshoring. To fill this gap, we present micro-level evidence on the robot-reshoring relationship using a representative panel of Spanish manufacturing firms from 2006 to 2017. By analysing this developed country, we provide empirical insights into the link between robot adoption and reshoring activities. This empirical analysis adds an important dimension to the existing literature and contributes to a better understanding of the interplay between robotisation and reshoring in the manufacturing sector. To the best of our knowledge, we also provide the first evidence that the adoption of robots in manufacturing firms within a developed country can stimulate reshoring activities not only from developing countries but also from other developed countries. We believe that the Spanish manufacturing industry is a relevant case study for this analysis, as according to the International Federation of Robotics' World Report (2021), Spain ranks fourth in industrial robotics installations in Europe (after Germany, Italy and France), and tenth in the world ranking. It has a robot density of more than 200 robots per 10,000 workers, significantly higher than the world average.

From a methodological perspective, our chapter utilises a combination of two-way fixed effects (TWFE) estimators and Difference-in-Differences (DiD) estimators with staggered adoption (Callaway and Sant'Anna, 2021). In our analysis, we treat robot adoption as the treatment variable and examine its effects on reshoring. The TWFE estimators help control for unobserved heterogeneity across firms, while the DiD estimators with staggered adoption help capture the dynamic relationship between robot

adoption and reshoring over time. By employing these methods, we aim to provide robust and reliable evidence on the causal relationship between robot adoption and reshoring.

The findings of our chapter suggest that there is no statistically significant reshoring from developing countries. This can be attributed to the fact that the productivity gains derived from robotics have not yet fully offset the cost differential between developed and developing countries, primarily driven by wage disparities. Furthermore, developing countries may have implemented measures to decrease wages in order to regain competitiveness in the global market. Conversely, our findings indicate that robotisation does lead to reshoring from developed countries, albeit only for a limited duration. This suggests that foreign suppliers of intermediate inputs in these countries require a certain amount of time to adapt and invest in robotisation themselves. This adaptation process entails acquiring the necessary technology and expertise to effectively integrate robotics into their operations.

Therefore, regarding policy implications, this study does not confirm that automation in a developed country substitutes developing country intermediate inputs, but rather the intermediate inputs from other developed countries, and this substitution is temporary until developed countries react. In principle, our findings may offer some relief for developing countries regarding the impact of robotisation. However, we cannot determine from this study whether this is due to a downward adjustment of their wages in response to competitiveness loss. Nonetheless, if the adoption of robotisation in one developed country prompts other developed countries to follow suit and regain competitiveness, it could result in an uncertain escalation of robotisation. Furthermore, our study highlights that reshoring resulting from robotisation in a developed country can occur through the substitution of foreign suppliers with in-house production. This

reshoring can contribute to employment and plays a critical role in the ongoing debate concerning the trade-off between robotisation and employment.

## 4.2. Theoretical background and hypotheses

It is an established fact that the expansion of global value chains seems to have come to a halt in recent years (Rodrik, 2018) and that the global fragmentation of production has been decreasing (Timmer et al., 2016). These recent trends may be due to the reshoring of the production of intermediate inputs (or of the tasks that produce certain intermediate goods) from developing to developed countries. The robotisation of firms in developed countries may have contributed to this.

From a development perspective, the robotisation of manufacturing firms in developed countries may have negative effects on the participation in global value chains of developing country firms that supply them with intermediate inputs (Faber, 2020).[80,81] Moreover, this comparative advantage may be further reduced or even lost when robotisation in developed country firms generates efficiency gains that increase productivity and reduce production costs (Graetz and Michaels, 2018; Acemoglu et al., 2020; Stiebale et al., 2020; Koch et al., 2021; Alguacil et al., 2022). A recent paper by Krenz et al. (2021) develops a theoretical framework relating reshoring to automation. Their model predicts that productivity improvements in automated processes lead to the reshoring of previously offshored production back to the home economy. They also provide empirical evidence for their predictions. In particular, for a panel of countries over the years 2000-2014, they construct a measure of reshoring activity at the macroeconomic level using the World Input-Output Database (WIOD) that is combined

[80] Materials, parts and components or tasks that produce certain intermediate goods.

[81] Faber (2020) shows evidence that robotisation in the United States coexists with reductions in exports from Mexico to the United States, which is interpreted as robotisation in a developed country encouraging reshoring from a developing country. He uses industry-year data and information on local labour markets.

with information on robot stocks from the International Federation of Robotics (IFR). They find evidence of automation-driven reshoring.

Therefore, if the lower unit costs of production resulting from robotisation compensate for the wage differential with developing countries, it is possible that there will be a relocation of production from developing to developed countries (Rodrik, 2018). In this chapter, we argue that such relocation is even more likely in the context of imports of intermediate inputs from developed countries. This is because the wage differential between developed countries is narrower, making it easier for firms to offset it through the implementation of robotisation technologies. As a result, the lower production costs resulting from robotisation can make it economically viable and advantageous for firms to relocate their production from developed countries to the home country, which is also developed. Robotisation is more likely to reduce the unit costs of firms in a developed country below the level of firms in other developed countries, rather than below that of firms in developing countries. Moreover, firms in these other developed countries are also less inclined to accept a reduction in wages as a means to regain their competitiveness following robotisation in the importing country.

Although the limited number of studies linking robots and reshoring at the macro level (Faber, 2020; Krenz et al., 2021) conclude that robotisation results in a substitution of offshored production with domestic production, they do not differentiate between whether this substitution involves foreign suppliers being replaced by domestic suppliers or the absorption of this production by the firms that initially offshored it. However, some studies on reshoring per se, i.e. without taking into account whether or not reshoring is a consequence of robotisation or new technologies, break down the measure of reshoring in such a way that it is possible to shed light on this point (Díaz-Mora et al., 2007; Castellani et al., 2013; Fuster et al., 2020). In our chapter, we follow this approach and

measure reshoring rates at the firm level (as a reverse process of offshoring) in line with previous literature at the sectoral level, i.e. as the ratio of imported intermediate inputs to the value of output, and then decompose this measure into two components. The first measures the share of imported intermediate inputs in total intermediate inputs used. The second measures the share of total intermediate inputs in the total value of output. A decrease in the non-decomposed index, reshoring, may be due to the substitution of foreign suppliers by domestic ones and/or to a lower fragmentation of production when imported intermediate goods are substituted by the firm's own production. Differentiating between the two phenomena is the purpose of the decomposition of Díaz-Mora et al. (2007), Castellani et al. (2013) and Fuster et al. (2020), which we employ in our chapter using firm-level data.[82]

Works providing firm-level evidence on the relationship between robotisation and reshoring are indeed scarce. However, two studies shed some light on this topic. Unlike us, both studies assume that if intermediate production conducted abroad is reshored, it would originate from countries with low labour costs. Therefore, they focus on the effects on imports from non-EU and non-OECD countries. One of them is Stapleton et al. (2023), which conducted a study on Spanish manufacturing. Their findings challenge the prevailing belief that automation drives reshoring. They found that robot adoption increases both the value of imports from lower-income countries and its ratio over production, although the latter result is weakly significant. In contrast, Alguacil et al. (2022), using the same data, found that robots have no effect on imports from developing

[82] Díaz-Mora et al. (2007) use country and sector data to analyse the decomposition of the index for Spain during the period 1995-2004. Castellani et al. (2013) use input-output tables for 21 European countries from 1995 to 2006 to decompose the reshoring index. Fuster et al. (2020) use sectoral data to show the reshoring of services in the Spanish economy since the onset of the Great Recession. In their analysis, they find that foreign sourcing was substituted by both internal production within the firm and by domestic suppliers.

countries. It is important to note that Stapleton et al. (2023) analysed data from 1990 to 2016, while Alguacil et al. (2022) focused on the period from 1990 to 2014. For developing countries, our research aligns with the findings of Alguacil et al. (2022), although we employ different methodologies, cover a different time span, and have a distinct focus in our chapter.[83] Additionally, unlike the previous studies, our analysis only considers data from 2006 onwards, as this is when firm-level information on imports of intermediate inputs is available. Therefore, we do not have to assume that firms' total imports are necessarily imports of intermediate inputs. We specifically focus on these imports instead of considering overall firm-level imports in order to provide a more precise measurement of reshoring. Furthermore, it is worth noting that the robots used from 2006 onwards are likely to be more sophisticated, technologically superior, and complex compared to those used in the 1990s.

Finally, although it is not the main focus of our chapter, what has been said in the literature about the joint effects of robotisation and reshoring on employment? On the one hand, there are studies on the effects of robots on employment. Acemoglu and Restrepo (2020) examine the effect of robots on employment in the United States using data on local labour markets and conclude that robots reduce employment. Dauth et al. (2021), also using local labour markets data, conclude for Germany that robots have a negative effect on employment in the manufacturing sector. However, other cross-country sectoral analyses of robot penetration and employment show mixed results (see the survey in Mondolo, 2022). A drawback of conducting analysis at the aggregate level is the lack of control for heterogeneity across individual firms. To address this limitation, there has been limited recent research that focuses on the adoption of robots using firm-level data.

[83] Their work focuses mainly on examining the impact of robot adoption on exports.

The earliest study on the firm-level effects of robot adoption on employment is indeed documented in a report by Jäger et al. (2015), which indicates that no significant effects of robots on employment were observed at the firm level. However, recent studies have provided mixed results on the impact of robot adoption at the firm level. For example, Acemoglu et al. (2020) and Dixon et al. (2020, 2021) conclude that robotisation increases total employment in firms that adopt robots.[84] Bonfiglioli et al. (2020) conclude that, after an initial positive demand shock due to robotisation, this process decreases employment.[85] Koch et al. (2021) find that robot adoption leads to net job creation in Spanish manufacturing firms, while Alguacil et al. (2022) using the same data, find no effect of robot adoption on firm-level employment. As summarised in Mondolo (2022), firm-level studies mostly find a positive or no effect on employment in robotised firms. However, studies at the aggregate level mostly find a net negative effect on employment. The literature on the effects of robot adoption on employment suggests that it has both positive and negative effects. The positive effect occurs if robots can increase productivity and efficiency, leading to increased output and employment. The negative effect occurs when there is a displacement effect whereby robots replace human workers. Ultimately, which effect dominates may depend on various factors, making it an empirical question.

On the other hand, there is a scarcity of studies focusing on the employment effects of reshoring. It is reasonable to anticipate that if foreign suppliers are substituted by domestic production, it may lead to an increase in domestic employment. However, studies like Fuster et al. (2020) have found no empirical evidence of the effect of reshoring on employment using industry-level data from Spain. For an overview of the empirical literature on the employment effects of offshoring, Hummels et al. (2018) provide a

[84] Acemoglu et al. (2020) use fiscal and administrative data on French manufacturing firms. Dixon et al. (2020, 2021) use information on robot imports for Canadian firms.
[85] Bonfiglioli et al. (2020) use information on robot imports for French firms.

survey. They conclude that there is significant variation in the results depending on whether the studies are conducted at the industry or firm level. The differences can be understood since, for example, when working with firm-level data, the substitution of foreign suppliers by domestic production will only increase the reshoring firm's output and employment if it is produced in-house, and not if it is replaced by domestic suppliers.

Furthermore, there is a notable lack of studies examining the impacts of robotisation-induced reshoring on firm employment, with very few or no existing research in this area. Our argument posits that even if robotisation were to result in job displacement through the substitution of human labour with robots (as suggested by Frey and Osborne, 2017), it is possible that through the process of reshoring, tasks previously conducted abroad are replaced by tasks performed domestically, leading to an increase in employment. However, with industry-year data Faber (2020) reveals that robotisation in the United States negatively affects employment in Mexico by promoting reshoring between 2000 and 2015 (not in the period 1990-2000), although no noticeable impact on US employment is observed. Additionally, using country-sector level data De Backer et al. (2018) find that robots in developed countries, particularly OECD countries, appear to slow down offshoring rates but do not incentivise firms to bring jobs back to their home countries.

We contribute to this final strand of the literature by introducing the possibility that the reshoring of tasks from foreign countries to the home country, facilitated by robotisation, can mitigate the displacement effect on employment caused by robots. In addition, we explore the scenario in which reshoring is carried out by firms that adopt robotics. In this case, it is possible that some of the recovered production, which leads to increased employment, may require fewer workers if a portion of the new production is performed by robots.

Based on the above considerations, we formulate the following working hypotheses in this chapter:

**H.1**: *Robot adoption will lead to the reshoring of activities back to developed countries.*

**H.2**: *Robot adoption drives reshoring of activities from developing countries or from other developed countries back to developed countries. This reshoring process depends on factors such as the initial wage differential (production costs), the impact of robotisation on production costs, and the response of wages or robotisation in the countries where offshoring originally occurred.*

**H.3**: *Robot adoption can lead to the reshoring of production activities from foreign suppliers to within the firm. This shift occurs when firms utilise robots to perform tasks internally instead of offshoring them. By adopting robots, firms can increase their efficiency and capabilities, allowing them to bring production back in-house and reduce reliance on external suppliers.*

**H.4**: *When reshoring is accompanied by the substitution of foreign suppliers with internal production within the firm, it is generally expected to have a positive effect on firm employment. However, when reshoring is combined with robot adoption, there can be a negative effect on employment, which offsets some of the positive gains. This occurs when a portion of the increased production resulting from reshoring is performed by robots instead of workers.*

## 4.3. Data and descriptives

### 4.3.1. Data sources and variables

In this chapter, we use a firm-level panel dataset obtained from the Spanish Survey of Business Strategies (ESEE) for the period 2006-2017.[86] We use a main working sample of 12,252 observations that corresponds to 1,825 firms. The ESEE is an annual survey, sponsored by the Spanish Ministry of Industry and conducted by the SEPI Foundation, which is representative (by industry and size) of the manufacturing sector in Spain.[87]

Since our main interest is to study whether robot adoption leads to reshoring, we will begin by explaining how we measure reshoring and robot adoption. First of all, our main dependent variable is reshoring, and we will measure it using an index that has been frequently used in the literature, albeit usually at the sector-country level (see, for instance, Michel and Rycx, 2012; Castellani et al., 2013; or Fuster et al., 2019, 2020). This reshoring index is defined as the proportion of imported intermediate inputs (II) relative to the value of production (Y). Therefore, it can be expressed as:

$$Reshoring\ index_{it} = \frac{II_{it}}{Y_{it}} \qquad (4.1)$$

where $II_{it}$ is the value of imported intermediate inputs of a firm *i* at time *t* in real terms, deflated using a firm-level deflator for intermediate inputs, and $Y_{it}$ is the value of production of a firm *i* at time *t* in real terms, deflated using a firm-level deflator for production.[88] According to this index, reshoring is defined as the reverse process of offshoring, which means that previously offshored tasks (or intermediates production

[86] Although the survey started in 1990, we are using data from 2006 because one of our variables of interest is only available from that year. Specifically, this applies to the reshoring index, which requires information on imports of intermediate inputs.

[87] More information in https://www.fundacionsepi.es/investigacion/esee/spresentacion.asp

[88] The base year for deflating the value of imported intermediate inputs and the value of production is 2006, which is the first year with data available in the ESEE database regarding intermediate inputs imports.

done abroad) are moved back to the home country (Faber, 2020). Hence, an increase in the index implies a higher dependence on imported inputs, signalling an increase in offshoring activity. Conversely, a decrease in the index indicates reshoring activities (Fuster et al., 2020).

Since this chapter also aims to consider the origin of imports of intermediate inputs, we take an additional step and differentiate them based on their sourcing origin. Specifically, we distinguish whether these imports originate from developed or developing countries. To accomplish this, we use the information collected in the survey, which categorises the origin of firms' imports into four region groups: EU, OECD excluding EU, Latin America, and the Rest of the World. We classify economies belonging to the EU or OECD as developed countries and those belonging to Latin America or the Rest of the World as developing countries.

Furthermore, as we are also interested in determining whether potential reshoring arises from the substitution of foreign suppliers with domestic suppliers or through production within the firm, we conduct a decomposition of the reshoring index (II/Y) into two components, following the approach used by Díaz-Mora et al. (2007), Castellani et al. (2013) and Fuster et al. (2020): (i) the proportion of imported intermediate inputs over the total intermediate inputs used (II/TI), and (ii) the total intermediate inputs used relative to the value of production (TI/Y). Thus, we can express the index in equation (4.1) as:

$$\frac{II_{it}}{Y_{it}} = \frac{II_{it}}{TI_{it}} \, x \, \frac{TI_{it}}{Y_{it}} \qquad (4.2)$$

where $II_{it}$ and $Y_{it}$ follow the same definition as before, and $TI_{it}$ is the total value of intermediate inputs, including both domestic and imported inputs, used by firm *i* at time *t*, in real terms, adjusted using a firm-specific deflator for intermediate inputs.

If there is a decrease in the reshoring index accompanied by a decrease in II/TI and TI/Y, we can infer that the firm is shifting from foreign suppliers to internal production. That is to say, the production of intermediate inputs is no longer in charge of foreign suppliers (decrease in II/TI), and additionally, it is being internalised by the firm, so it no longer relies on any suppliers (decrease in TI/Y). However, if there is a decrease in the reshoring index along with a decrease in II/TI, but TI/Y remains stable (or increases), it indicates that the firm is replacing foreign suppliers with domestic suppliers. This means that the production of intermediate inputs continues to be done outside the firm (TI/Y does not decrease), but now the supplier is domestic instead of foreign (decrease in II/TI).

We will now define the main explanatory variable in our chapter, which is robot adoption. To measure this, we construct a dummy variable that takes a value of 1 if a firm utilises robots in its production process and 0 if it does not. Although the survey is conducted yearly, information on this variable is available only every four years, starting from 1990. However, our study focuses on the period 2006-2017, as the data on intermediate inputs imports begins in 2006. To define our treatment variable, "robot first adopters", we also consider information from the previous waves. Specifically, we consider a firm as a robot starter if it starts using robots in year t but did not use them in the previous period (t-4), as indicated by the database. As a comparison group for treatment effects, we consider firms that never use robots (never treated). Our analysis focuses on firms transitioning from non-robot use to first-time robot use. Our baseline analysis includes firms that continuously use robots after initial adoption and those that use robots for a certain period and then abandon their use. This approach aligns with the baseline sample used in the study by Koch et al. (2021).[89] Furthermore, we conduct a

[89] With the same database, Koch et al. (2021) did not find significant differences between firms that continuously use robots and firms that use robots but abandon their use at some point in time.

robustness check by excluding firms that abandon robot use after a certain period. In this case, we use only firms that started to use robots and continuously report to use robots afterwards (also Koch et al., 2021, report such a robustness check).[90] Importantly, our results remain robust and consistent even when using this restricted sample.

Finally, although it is not the primary focus of the chapter, we are also interested in investigating the impact of robot adoption and reshoring on employment, specifically the effect of reshoring on employment for firms that have adopted robots. To measure employment, we will use the log of the firm's number of workers.

### 4.3.2. Descriptives

To provide some descriptive evidence related to the hypotheses we put forward in this chapter (see section 4.2), we will now conduct a descriptive analysis based on our sample. We start first with the evolution of the two main variables, i.e. robot adoption and the reshoring index. Thus, Table 4.1 contains the average value of these variables at the beginning and at the end of the sample period. As can be seen, while the number of robot users increased during the sample period,[91] reshoring activities increased, as evidenced by the decrease in the index (note that reshoring is defined as the reverse of offshoring and therefore a decrease in the index indicates reshoring). This shows a growth in the use of robots, but an upward trend in reshoring. However, there are notable differences in the evolution of reshoring between robot users and non-robot users. In particular, Table 4.2 shows the average annual growth in the reshoring index for robot users and non-robot users over the period. Table 4.2 displays that, for non-robot users, the reshoring index has decreased by an average of 2.59% per year during the analysis period. In contrast, for

[90] In both the baseline and robustness samples, we did not include firms that switched back and forth between robot use and non-use multiple times.
[91] Robot users are defined as firms using robots in their production processes at time t.

robot users, the reshoring index has experienced an average annual decrease of almost 5%. In summary, while there is an overall decline in the reshoring index (Table 4.1), this decline is more pronounced among robot users. This provides preliminary evidence for Hypothesis 1, which suggests that the adoption of robots is associated with an increase in reshoring activities.

Table 4.1. Mean robot use and reshoring index – Evolution.

| Robot use | | Reshoring index | |
|---|---|---|---|
| 2006 | 2017 | 2006 | 2017 |
| 0.297 | 0.331 | 0.223 | 0.161 |
| (0.457) | (0.471) | (0.322) | (0.251) |

Note: Standard Deviations are given in parentheses

Table 4.2. Annual growth of the reshoring index – Differences between robot users and non-robot users.

| Non-robot users | Robot users |
|---|---|
| -2.59 | -4.93 |
| (9.49) | (11.14) |

Notes: (i) Standard Deviations are given in parentheses (ii) The growth is calculated using the cumulative average annual growth rate (in percentage).

Secondly, we are interested in the origin of imports of intermediate inputs. In this respect, we note that around 80% come from developed countries, either from the EU or the OECD. However, although the majority come from these economic areas, reshoring activities may be driven by processes taking place in developed or developing countries, as indicated in Hypothesis 2. To shed some light on this issue, Figures 4.1 and 4.2 show the evolution of the reshoring index for robot users differentiating whether imports come from developed or developing countries. While Figure 4.1 shows an increasing trend of reshoring when imports originate from developed countries, this pattern is not observed when imports originate from developing countries. In the latter case, it is generally

observed that there may even be some increase in offshoring activities to these countries (which seems to be in line with Stapleton et al., 2023). Hence, what is clear is that the data suggest that reshoring predominantly comes from activities in developed countries.

Figure 4.1. Evolution of reshoring index for robot users – Imports from developed countries.

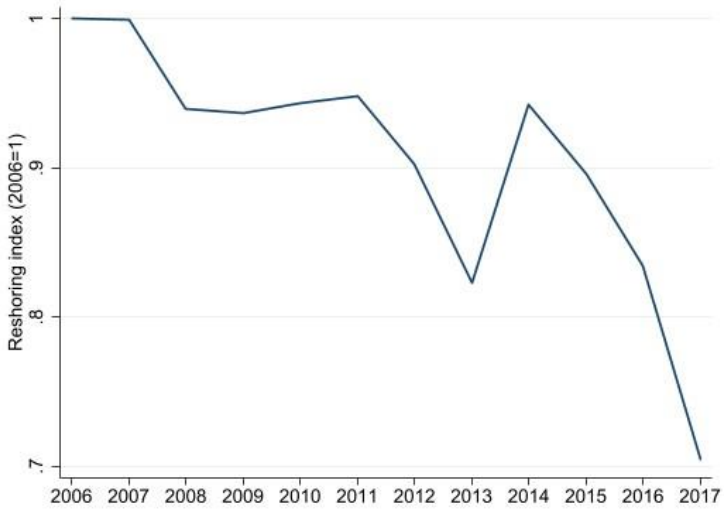
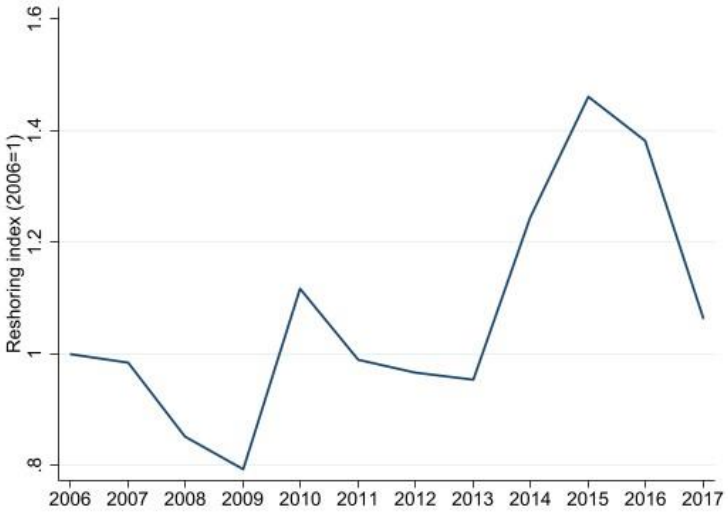



Figure 4.2. Evolution of reshoring index for robot users – Imports from developing countries.




Third, once we have shown evidence in the data of an increase in reshoring activities accompanied by an increase in the adoption of robots, what does the data say about who produces this reshored production? Is it produced by domestic suppliers or

internalised by the firm? To show some evidence on this question, we look at what happens to the two components into which the reshoring index (II/Y) can be divided according to equation (4.2): (i) II/TI, which is the ratio of imported intermediate inputs to total intermediate inputs, and (ii) TI/Y, which is the ratio of total intermediate inputs to output. A decrease in the overall index accompanied by a decline in both components indicates that the activities that are reshored are being produced internally within the firm. Table 4.3 presents the evolution of the index and its two components.

Table 4.3. Decomposition of the reshoring index – Annual evolution.

| | Annual variation 2006-2017 | | |
|---|---|---|---|
| | II/Y | II/TI | TI/Y |
| Overall | -2.59 | -1.99 | -2.35 |

Notes: The growth is calculated using the cumulative average annual growth rate (in percentage).

As shown in Table 4.3, there is evidence of a negative trend in the index and its two components. This confirms the earlier observation of an increase in reshoring activities. Additionally, the data suggests that foreign suppliers are being replaced by in-house production, indicating that reshoring activities are now being conducted within the firm. This trend is consistent across almost all manufacturing sectors of the economy, indicating a widespread pattern.[92] This evidence from the data aligns with Hypothesis 3, which suggests that reshoring potentially triggered by the adoption of robots can enable firms to enhance their efficiency and capabilities, making it viable for the reshored production to be internally produced.

Finally, we examine the data for evidence of the impact of firm-level reshoring on employment. On one hand, if reshoring involves replacing foreign suppliers with in-house production, we would expect a positive effect on employment. However, if reshoring is

[92] Table A4.1 in Appendix 4 displays the evolution of the reshoring index and its components broken down by sector.

driven by robot adoption, the increase in production may be partially undertaken by robots rather than workers, potentially mitigating the positive effect on employment. To shed some light on this matter, Table 4.4 presents the average number of workers per firm, distinguishing between firms that utilise robots and those that do not, as well as firms engaged in reshoring activities and those that are not.[93]

Table 4.4. Mean of number of workers.

| ROBOT USERS | | RESHORING | |
|---|---|---|---|
| YES | NO | YES | NO |
| 373.42 | 112.95 | 283.78 | 170.07 |
| (960.57) | (447.61) | (824.84) | (623.28) |

Notes: (i) Standard Deviations are given in parentheses

As shown in Table 4.4, both firms that use robots and firms engaged in reshoring tend to be larger. However, we claim that the effect on employment might differ if reshoring is driven by robot adoption. Based on our data, firms that engage in both reshoring and robot adoption experience an increase in the number of employees of 1.58% over the analysed period. In contrast, firms that reshore but never utilise robots experience a growth in the number of employees of 2.50%. This finding supports Hypothesis 4, indicating that firms that engage in both reshoring activities and robot utilisation experience a decrease in employment creation compared to firms that only engage in reshoring. This can be attributed to the fact that firms utilising robots employ them to perform specific tasks that are being reshored back to the firm.

## 4.4. Econometric strategy and results

Our primary objective is to assess the extent to which the adoption of robots facilitates reshoring, deepening on the origin of imports and breaking down the reshoring

[93] To convert the reshoring index into a binary variable for firm classification, we define a firm as reshoring when the growth rate of the reshoring index from one year to the next is negative.

activity. In this section, we will outline our empirical approach for addressing these questions and then we will present the results. To address them, we first employ the most widely used technique in economics to measure the effect of a treatment on an outcome, the "two-way fixed effects" (TWFE) estimator (Wooldridge, 2021). In our particular case, it consists of regressing firm i's reshoring index in period t, which is the outcome, on firm fixed effects, period fixed effects and the treatment variable indicating firm i's adoption of robots from the year of adoption. With this approach, we can take advantage of the panel structure of the data and account for the possible presence of unobserved heterogeneity and possible changes in the economic environment affecting firms. Therefore, the equation we estimate is as follows:[94]

$$Reshoring\ Index_{i,t} = \beta_0 + \beta_1 ROBOT_{i,t} + \delta_s + \delta_t + \delta_i + \epsilon_{i,t} \quad (4.3)$$

where $\delta_s$, $\delta_t$ and $\delta_i$ are industry, year and firm fixed effects. Estimating this equation, we can see the effect of robot adoption on the reshoring index. A negative sign of the parameter of interest $\beta_1$would imply that robot adoption leads to reshoring.

However, it is important to acknowledge the limitations of the TWFE estimation method, as there may be concerns regarding the interpretation of the results as causal effects. Additionally, the TWFE estimation considers that the treatment occurs for all firms at the same time.[95] However, we recognise that, in our case, firms do not all adopt robots at the same time. Each firm adopts robots at its own convenience, and this does not necessarily happen in the same year for all firms. It is therefore necessary to exploit the variation in treatment times, as firms may be treated at different times. In other words, it is necessary to take into account the variation in the timing of robot adoption. To do so,

[94] Note that we have also included industry fixed effects.

[95] For a further discussion of the limitations of the TWFE estimator, please refer to Callaway and Sant'Anna (2021).

we rely on Callaway and Sant'Anna (2021) difference-in-differences (DiD) estimator with staggered adoption.

The staggered DiD is an extension of the original idea of combining propensity score matching with DiD to estimate treatment causal effects. In the standard or more traditional case of Difference-in-Differences (DiD) analysis, the matching process is used to obtain a control group of firms' observations with an equal probability of receiving the treatment (in our case, adopting robots). Subsequently, a DiD analysis is conducted using the group of treated firms and their matched controls. This ensures that if treated firms and untreated firms have the same probability of being treated (based on a set of pre-treatment variables), any difference between the two groups after the treatment can be attributed to the treatment itself.

The extension introduced by the staggered DiD methodology involves conducting matching for each generation (cohort) of treated units, as they receive treatment at different times, and accounting for the dynamics of the causal effects of treatment over time. This methodology also enables the testing of parallel trends before the treatment period. That is to say, it allows to test whether the treatment and control groups were following parallel paths in the absence of treatment. Throughout the chapter we never reject the assumption of parallel trends, which is necessary to establish causal effects. In order to apply this methodology to our data, we employ the same specification as in equation (4.3), and additionally include a set of variables to facilitate the matching process between the treatment and control groups in the pre-treatment period.

Related to the matching procedure, each treated firm (robot adopter) is compared with potential control firms in the same year and in the same industry. Hence, after matching, any difference in the probability of adopting robots between treated and controls is expected to be random. To implement the matching, we select a set of firm’s

variables that have significant power to explain robot adoption. These are Total Factor Productivity, R&D investment, the share of skilled workers, capital intensity, exporter and importer status and size. Total Factor Productivity is derived from a Cobb-Douglas production function following Wooldridge (2009). We use the Gross Output approach, meaning that we are relating the measure of output of a firm to a function of capital, labour and intermediate inputs, and deflated by firm-level deflators (and therefore using a "quantity-based" production function). The R&D investment variable is a dummy variable that takes the value 1 if the firm has expenditure in R&D and 0 otherwise. The share of skilled workers is the share of engineers and personnel with a university degree. Capital intensity is the deflated capital stock per worker (in logs).[96] Exporter status is a dummy variable that takes the value 1 if the firm exports and 0 otherwise. Importer status is a dummy variable that takes the value 1 if the firm imports intermediate inputs and 0 otherwise. Size is a dummy variable that takes the value 1 if the firm is classified as a large firm, meaning it has more than 200 employees. Conversely, it takes the value of 0 if the firm is categorised as an SME, indicating it has 200 employees or less. In summary, the set of variables to implement the matching we use in our chapter is quite similar to previous works such as Koch et al. (2021) or Alguacil et al. (2022). These papers also use the ESEE but for a different time span and purpose, however, the qualitative results of the variables determining robot adoption are the same.[97]

As mentioned in section 4.3.1, to define our treatment variable (robot adopters), we will consider firms that have adopted robots and continuously use them, as well as firms

[96] To measure capital, we use capital stock in real terms constructed using the perpetual inventory method and based on current replacement value net of depreciation. Capital in real terms is obtained by deflating capital at current replacement values by the price index of investment. The price index of investment is obtained as the equipment goods component of the index of industry prices published by the Spanish National Institute of Statistics.

[97] Table A4.2 in Appendix 4 shows the results of a single global probit regression, confirming the explanatory power of the selected variables in explaining robot adoption.

that have stopped using them at some point in time. However, for the sake of robustness, we will also present results excluding firms that abandon the use of robots. Nonetheless, these firms are not prevalent in our sample, accounting for only 5% of the total number of firms.

To recapitulate, to address our objectives in this chapter we will combine the TWFE and the staggered DiD estimators. We start with Tables 4.5 and 4.6, which show the results that will allow us to answer our first question: does the adoption of robots lead to reshoring?

Table 4.5. Does robot adoption lead to reshoring? – TWFE.

| | (1)<br>II/Y |
|---|---|
| Robots | -0.023**<br>(0.011) |
| Observations | 12,252 |

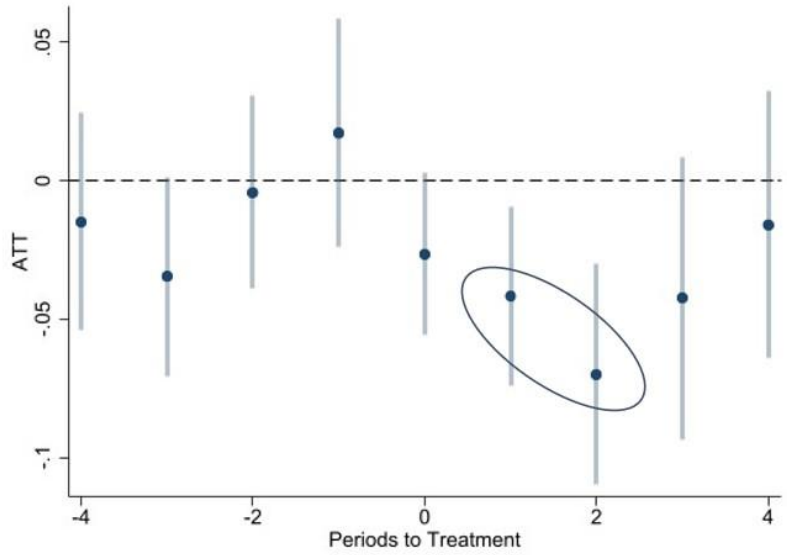
Notes: Robust standard errors in parentheses clustered by firm (ii) ** p<0.05 (iii) All regressions include firm, industry and year fixed effects.

Table 4.6. Does robot adoption lead to reshoring? – Staggered DiD (ATT).

| | (1)<br>II/Y |
|---|---|
| Robots | -0.046***<br>(0.017) |
| Observations | 12,252 |
| Pretend test | -0.004<br>(0.011) |

Notes: (i) Doubly robust inverse probability weighting method used for estimating standard errors (Sant'Anna & Zhao, 2020) (ii) *** p<0.01 (iii) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, if we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure 4.3. ATT – Robot adoption on reshoring index.




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Table 4.5 shows the results using the TWFE estimator, while Table 4.6 displays the results for the staggered DiD. In both cases it is confirmed that there is a negative effect of robot adoption on the reshoring index. That is, when firms adopt robots, they tend to bring back production that was previously produced abroad. Particularly, Table 4.6 presents the ATT (Average Treatment Effect on the Treated), which is negative and significant as aforementioned. However, it is also relevant to look at Figure 4.3 since it shows the dynamic effect of robot adoption on the reshoring index.[98] In particular, the increase in reshoring is observed to last for two years after the adoption of robots. This suggests that firms in countries from which activities are reshored may be reacting in response to a loss of competitiveness. Their ability to react may take some time, but when it occurs, it may render the importing country firm's reshoring strategy unfavorable. This result is also confirmed if we drop from the sample the firms that abandon the use of

[98] For all Figures representing the results of the staggered DiD, we will present 4 years before treatment and 4 years after, as this fully captures the effects before and after treatment (however, we are considering for estimation the entire period 2006-2017).

robots at some point in time. Results for this more restricted sample are in Table A4.3 and Figure A4.1 of Appendix 4. Hence, we confirm our Hypothesis 1: Robot adoption leads to reshoring activities, bringing back production to developed countries, as we illustrate in this case for Spain.

Now, let us delve into the following questions addressed in this chapter: Where does reshoring originate from? Do firms primarily bring back production from developed or developing countries? To shed light on these questions, we analyse the effects of robot adoption on reshoring by distinguishing the origin of imports of intermediate inputs. The results are presented in Tables 4.7 and 4.8. In these tables, we conduct the baseline regression specified in equation (4.3) and corresponding staggered DiD estimations using the proportion of imports originating from developed or developing countries within each firm. Imports are categorised as originating from developed countries if they come from EU or OECD countries, while imports from Latin American countries or the rest of the world (not including EU or OECD) are classified as originating from developing countries.

Table 4.7. Does robot adoption lead to reshoring? Importing intermediates from developed or developing countries. – TWFE.

| | Importing intermediates from developed countries | Importing intermediates from developing countries |
|---|---|---|
| | (1) | (2) |
| | II/Y | II/Y |
| Robots | -0.023** | 0.009 |
| | (0.011) | (0.008) |
| Observations | 12,019 | 12,023 |

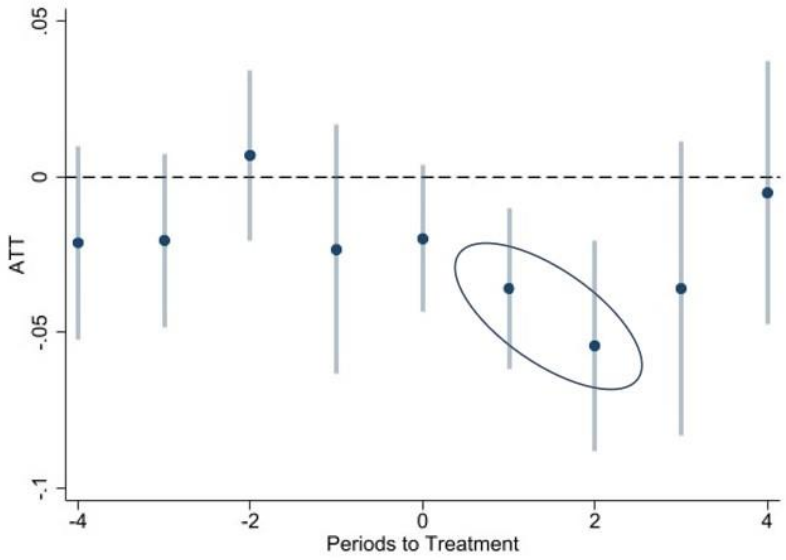
Notes: (i) Robust standard errors in parentheses clustered by firm (ii) ** p<0.05 (iii) All regressions include firm, industry and year fixed effects.

Table 4.8. Does robot adoption lead to reshoring? Importing intermediates from developed or developing countries. – Staggered DiD (ATT).

| | Importing intermediates from developed countries | Importing intermediates from developing countries |
|---|---|---|
| | (1)<br>II/Y | (2)<br>II/Y |
| Robots | -0.037***<br>(0.013) | 0.011<br>(0.015) |
| Observations | 12,019 | 12,023 |
| Pretend test | 0.003<br>(0.010) | 0.000<br>(0.005) |

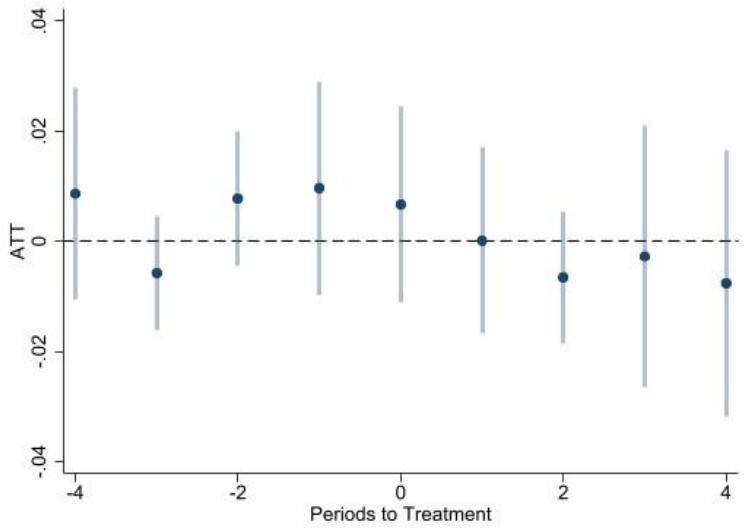
Notes: (i) Doubly robust inverse probability weighting method used for estimating standard errors (Sant'Anna & Zhao, 2020) (ii) *** p<0.01 (iii) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, if we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure 4.4. ATT – Robot adoption on reshoring index (importing intermediates from developed countries).




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Figure 4.5. ATT – Robot adoption on reshoring index (importing intermediates from developing countries)




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Tables 4.7 and 4.8 confirm that reshoring activities primarily stem from processes previously conducted in developed countries, while no evidence of reshoring is found for production that originated in developing countries. This provides an answer to our Hypothesis 2: the adoption of robots in a developed country like Spain leads to the reshoring of activities that were previously carried out in developed countries. It appears that the adoption of robots enables Spanish firms to reduce production costs, thereby increasing the economic viability of relocating production to the home country. Moreover, this likelihood is higher when the production was initially offshored to developed countries, as the smaller wage differential between Spain and other developed countries makes it easier to overcome the cost difference once the firm adopts robots. On the contrary, there is typically a larger wage gap with developing countries, which poses challenges for Spanish firms to achieve lower production costs even with the adoption of robots. Furthermore, even if they were able to bridge the gap, developing countries are

more inclined than developed countries to reduce their wages in order to regain cost competitiveness.

Figure 4.4 presents the dynamic effects of robot adoption on reshoring coming from developed countries. In this case we confirm that the effect in reshoring activities lasts two years after the adoption of robots. However, as shown in Figure 4.5, there is no significant effect on offshored activities in developing countries. These results hold even when firms that stop using robots at a point in time are excluded from the sample, as shown in Table A4.4 and Figures A4.2 and A4.3 in Appendix 4.

Furthermore, we aim to strengthen the previous findings on the origin of reshoring by conducting an analysis that employs an alternative definition of importing from developed or developing countries. This alternative approach enables us to categorise firms into two distinct groups based on their primary import sources. Consequently, we can assess the influence of robotisation on firms that primarily import from developed countries and those that predominantly import from developing countries.[99] The findings from Tables A4.5 and A4.6, as well as Figures A4.4 and A4.5 in Appendix 4, further support the notion that reshoring is indeed happening from activities previously conducted in developed countries. By employing this alternative definition of import origins, it becomes evident that reshoring is exclusively observed in firms that primarily imported from developed countries. These results reinforce the idea that the phenomenon of reshoring is primarily driven by firms that had previously offshored their activities to developed countries but are now bringing them back to their home country.

[99] We consider a firm to import mainly from developed countries if more than 50% of its imports originate from EU or OECD countries. Conversely, we classify a firm as importing mainly from developing countries if more than 50% of its imports come from Latin American countries or other countries that are not part of the OECD or EU.

The next question raised in the chapter is whether, once a firm reshored, it replaces foreign suppliers with domestic suppliers or with internal production. To address this question, we can utilise the decomposition of the reshoring index, as shown in equation (4.2). The reshoring index (II/Y) was divided into two components: (i) the proportion of imported intermediates over total intermediates used (II/TI) and (ii) the total intermediates used in relation to the value of production (TI/Y). Tables 4.9 and 4.10 show the effects of robot adoption on the two components of the reshoring index.

Table 4.9. Effect on the decomposition of the reshoring index – TWFE.

| | (1)<br>II/TI | (2)<br>TI/Y |
|---|---|---|
| Robots | -0.031*<br>(0.017) | 0.000<br>(0.006) |
| Observations | 12,251 | 11,983 |

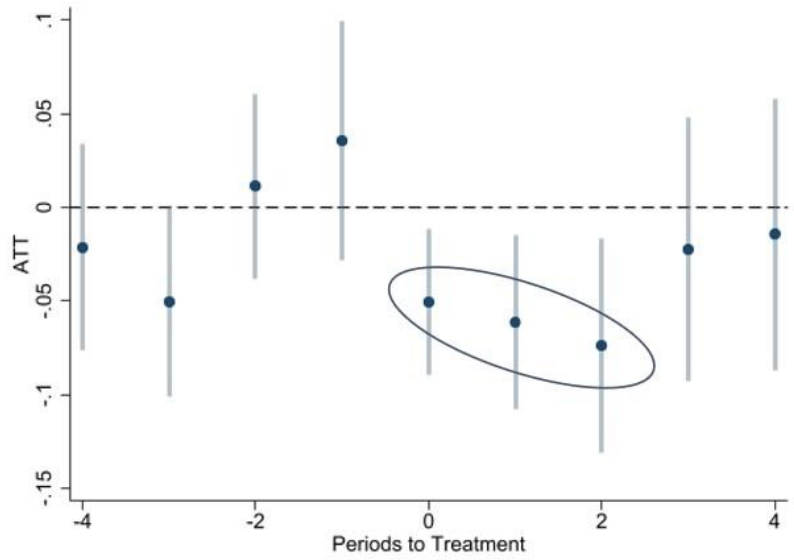
Notes: (i) Robust standard errors in parentheses clustered by firm (ii) * p<0.1 (iii) All regressions include firm, industry and year fixed effects.

Table 4.10. Effect on the decomposition of the reshoring index – Staggered DiD (ATT).

| | (1)<br>II/TI | (2)<br>TI/Y |
|---|---|---|
| Robots | -0.062***<br>(0.021) | -0.021**<br>(0.011) |
| Observations | 12,251 | 11,977 |
| Pretend test | -0.004<br>(0.015) | -0.005<br>(0.004) |

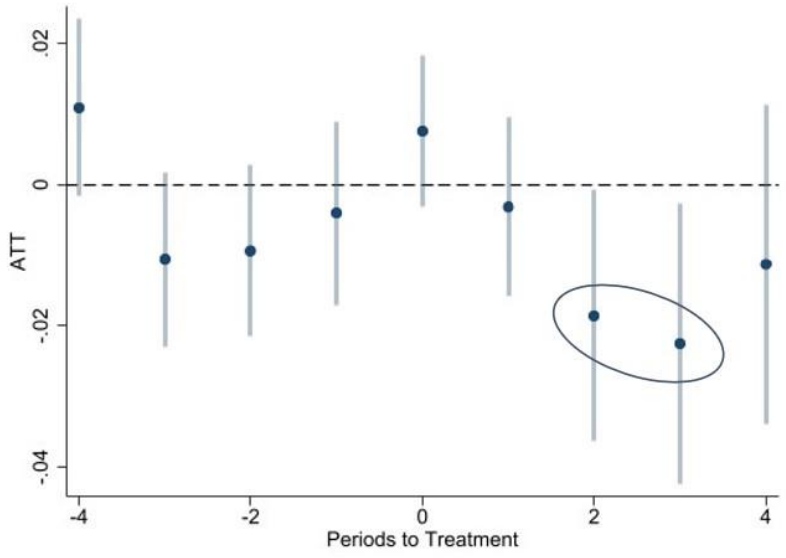
Notes: (i) Doubly robust inverse probability weighting method used for estimating standard errors (Sant'Anna & Zhao, 2020) (ii) *** p<0.01, ** p<0.05 (iii) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, if we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure 4.6. ATT – Robot adoption on II/TI.




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Figure 4.7. ATT – Robot adoption on TI/Y.




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

While Table 4.9, which utilises the TWFE estimator, reveals an effect only on the II/TI component, the staggered DiD analysis presented in Table 4.10 confirms that robot

adoption negatively impacts both components of the reshoring index, namely II/TI and TI/Y. This finding suggests that firms adopting robots are indeed substituting foreign suppliers with internal production. In other words, tasks that were previously offshored and performed abroad are now being brought in-house and carried out within the firm, facilitated by the adoption of robots. Figures 4.6 and 4.7 confirm that this effect is also time-limited. Likewise, Table A4.7 and Figures A4.6 and A4.7 in Appendix 4 support these results excluding firms that stop using robots at some point in time. Thus, we confirm our Hypothesis 3: Robot adoption helps firms perform production tasks in-house instead of outsourcing them. This may be possible thanks to the increased efficiency and capabilities offered by robots.

One final issue to consider is the potential impact of robots on marginal costs and, consequently, on TFP. If robots reduce marginal costs, they can boost a firm's TFP. In such instances, one might question whether the observed decrease in intermediates, including imports, could be attributed to the rise in TFP resulting from decreased marginal costs rather than to reshoring. To establish this, it should be determined whether, as firms enhance their TFP, there is not a concurrent market expansion stemming from the efficiency gains. However, if firms become more efficient in production and expand their production and sales, they would increase their need for intermediate inputs.

To examine which mechanism is more likely to be at play in our case, we conducted various TWFE regressions (all including industry, year, and firm fixed effects). Firstly, we regressed firm TFP on robot adoption and found a positive effect (see Table A4.8 in Appendix 4), consistent with previous studies by Koch et al. (2021), Alguacil et al. (2022), and Stapleton et al. (2023). Secondly, to address the concern that the decrease in the ratio of imported intermediates or total intermediates to output could be driven by firms requiring fewer intermediates to produce when they become more efficient, we

regressed the reshoring index, the log of imported intermediate inputs, and the log of total firm intermediated inputs on both the robot adoption dummy and firm TFP. These regressions were repeated with different dependent variables, including the ratio of imported intermediate inputs from developed countries to output, the log of imported intermediate inputs from developed countries, and the same two variables for developing countries. The results, presented in Table A4.9 in Appendix 4, indicate that robot adoption maintains its negative effect on the share of imported intermediates in output and on the log of imported intermediates after controlling for TFP, and that this also holds true when specifically examining developed countries. However, robot adoption does not significantly affect reshoring or the log of imported intermediate inputs from developing countries. Results suggest that the negative effect of robot adoption on imports of intermediate inputs and the share of imported intermediates in output is not driven by robots increasing TFP and consequently reducing the firm's needs for intermediates. Conversely, the positive effect of TFP on the share of imported intermediates in output and the log of intermediate inputs, regardless of origin, suggests that an increase in TFP leads to firm output expansion. Therefore, when robot adoption enhances TFP, rather than reducing the firm's need for intermediate inputs given its improved efficiency in producing a given output, it increases it due to a firm's market expansion. Thus, a TFP increase resulting from robotisation would not invalidate our finding that robot adopters increase reshoring and reduce imports of intermediate inputs relative to production, primarily from developed countries.

To support the existence of market expansion, we further regressed the log of firm sales on robot adoption (see Table A4.8 in Appendix 4) and found a positive effect of robots on sales, as observed in Stapleton et al. (2023). In summary, our findings support a positive effect of robots on TFP. However, since they also drive output expansion for

the firm, this would result in the firm requiring more intermediate inputs, not fewer. Therefore, it is not that the firm is reducing imports of intermediate inputs because it is becoming more productive by using robots, but rather because it is reshoring, as now robots can produce within the firm some of the intermediate products that were previously imported. Hence, while a productivity improvement typically yields two effects: i) enabling the production of the same level of output with fewer inputs, and ii) reducing marginal costs, thereby incentivising increased production and the need for more inputs, in our case, the market expansion effect dominates.

Finally, the validation of our Hypothesis 3 brings us to the last question addressed in this chapter. Given that robot adoption contributes to reshoring and involves the substitution of foreign suppliers with internal production within the firm, we now examine the effect of robotisation-induced reshoring on firms' employment. To address this question, we estimate a TWFE regression that can be expressed as follows:

$$LN(WORKERS)_{i,t} = \beta_0 + \beta_1 ROBOT_{i,t} + \beta_2 GROWTH\_RESHORING\_INDEX_{i,t} + \beta_3 ROBOT_{i,t} \times GROWTH\_RESHORING\_INDEX_{i,t} + \delta_s + \delta_t + \delta_i + \epsilon_{i,t} \quad (4.4)$$

Where $LN(WORKERS)_{i,t}$ is the logarithm of the number of workers of a firm *i* at time *t,* $ROBOT_{i,t}$ is the dummy variable that takes the value 1 if the firm adopts robots (the same that was used before), $GROWTH\_RESHORING\_INDEX_{i,t}$ is a dummy variable that takes the value 1 if there is a negative growth of the reshoring index, i.e., it takes the value 1 when the firm *i* at time *t* does reshoring and 0 otherwise, and $ROBOT_{i,t} \times GROWTH\_RESHORING\_INDEX_{i,t}$ is the cross product of both variables. Table 4.11 displays the estimation results for equation (4.4).

Table 4.11. Effect of robot adoption and reshoring on employment

| | WORKERS |
|---|---|
| $ROBOT_{i,t}$ | 0.030** |
| | (0.014) |
| GROWTH RESHORING $INDEX_{i,t}$ | 0.015** |
| | (0.007) |
| $ROBOT_{i,t}$ × GROWTH RESHORING $INDEX_{i,t}$ | -0.020* |
| | (0.011) |
| Constant | 4.070*** |
| | (0.005) |
| Observations | 17,576 |

Note: (i) Robust standard errors in parentheses (ii)*** p<0.01, ** p<0.05, * p<0.1 (iii) Clustered by firm (iv) All regressions include firm, industry and year fixed effects.

According to the results presented in Table 4.11, we find evidence that robot adoption has a positive impact on firm-level employment, consistent with previous studies such as Koch et al. (2021). Similarly, reshoring also shows a positive effect on employment, as it involves bringing production back within the firm, which may require hiring additional workers to meet increased production demands. However, when considering the interaction between robot adoption and reshoring (the cross product), we observe a negative effect. This suggests that while firms adopting robots and engaging in reshoring bring production back to the firm, a portion of this production is carried out by robots rather than human workers, supporting our Hypothesis 4.

## 4.5. Conclusions

This chapter aims to examine and provide novel evidence on the impact of firms' adoption of robots on reshoring activities within a developed country. The study differentiates between reshoring activities from developed and developing countries and examines whether it takes place through the substitution of foreign suppliers with domestic suppliers or through internal production. Furthermore, the analysis explores the effect of robotisation-induced reshoring on firms' employment. To estimate causal effects, the study utilises a combination of two-way fixed effects and Difference-in-Differences

(DiD) estimators with staggered adoption. The data used for the analysis is derived from a representative panel of Spanish manufacturing firms covering the period from 2006 to 2017. The findings suggest that the adoption of robots leads to reshoring, primarily from developed countries, driven by the substitution of foreign sourcing with internal production. This supports the conclusion of the chapter that reshoring contributes to increase firm employment. However, the positive effect on employment is somewhat diminished when reshoring is accompanied by robot adoption, as robots are likely involved in the production of a portion of the reshored goods within the firm.

To the best of our knowledge, this chapter represents the first comprehensive analysis that examines the effects of robot adoption on reshoring using firm-level data for both robot use and reshoring measures. Previous studies on this topic have been limited in their scope, mainly relying on country-sector data and lacking a detailed examination of the firm-level dynamics. Additionally, these studies did not differentiate between the sourcing origins at the firm level nor explore whether reshoring involved the substitution of foreign suppliers through in-house production or domestic suppliers. Thus, this chapter fills a significant research gap by conducting a thorough analysis of the relationship between robot adoption and reshoring. In addition, it also goes a step further by examining the combined effect of robotisation and reshoring on firms' employment. By investigating the interplay between these two phenomena, the chapter offers valuable insights into how they jointly shape employment within firms. This holistic approach provides a more comprehensive understanding of the complex interactions between robotisation, reshoring, and employment outcomes, making a valuable contribution to the limited body of literature in this field.

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# APPENDIX 4

Table A4.1. Decomposition of the reshoring index – Evolution by sector.

| | Annual Percentage variation 2006-2017 | | |
|---|---|---|---|
| | II/Y | II/TI | TI/Y |
| Meat products | -2.76 | -2.65 | -3.81 |
| Food and tobacco | -3.37 | -2.53 | -2.19 |
| Beverage | -2.57 | -2.87 | -1.22 |
| Textiles and clothing | -3.75 | -2.95 | -2.42 |
| Leather, fur and footwear | -1.06 | -1.10 | -2.02 |
| Timber | -1.39 | -1.22 | -3.62 |
| Paper | -1.91 | -1.13 | -1.22 |
| Printing (before Printing and Edition) | -0.75 | -0.40 | -2.41 |
| Chemicals and pharmaceuticals | -2.96 | -2.07 | -2.28 |
| Plastic and rubber products | -1.91 | -0.99 | -2.71 |
| Nonmetal mineral products | -4.67 | -4.73 | -1.22 |
| Basic metal products | -2.40 | -2.72 | -0.46 |
| Fabricated metal products | -1.17 | -0.63 | -2.58 |
| Machinery and equipment | -4.03 | -3.23 | -2.82 |
| Computer products, electronics and optical | 0.39 | 1.64 | -2.56 |
| Electric materials and accessories | -1.83 | -0.85 | -2.01 |
| Vehicles and accessories | -4.96 | -4.27 | -1.66 |
| Other transport equipment | -6.26 | -5.92 | -2.94 |
| Furniture | -1.36 | -0.91 | -1.36 |
| Other manufacturing | -4.03 | -3.18 | -1.82 |

Note: The growth is calculated using the cumulative average annual growth rate (in percentage).

Table A4.2. Probit regression before matching – What affects robot adoption?

| | Robot adoption |
|---|---|
| TFP | 0.239*** |
| | (0.027) |
| Size | 0.167** |
| | (0.070) |
| R&D investment | 0.151*** |
| | (0.052) |
| Skilled staff | -0.007** |
| | (0.003) |
| Import of intermediates | 0.069† |
| | (0.044) |
| Export | 0.117** |
| | (0.059) |
| Capital intensity | 0.193*** |
| | (0.026) |
| Constant | -6.122*** |
| | (0.367) |
| Observations | 17,632 |

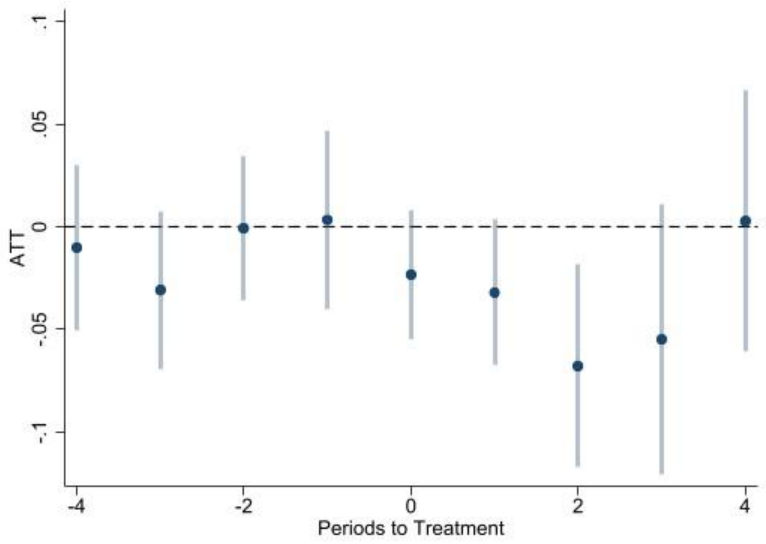
Notes: (i) Robust standard errors in parentheses clustered by firm (ii) *** p<0.1, ** p<0.05, † slightly below p<0.1 (iii) All regressions include industry and year fixed effects.

Table A4.3. Does robot adoption lead to reshoring? – Staggered DiD excluding firms that abandon robot use (ATT).

| | II/Y |
|---|---|
| Robots | -0.041** |
| | (0.018) |
| Observations | 11,231 |
| Pretend test | -0.005 |
| | (0.011) |

Notes: (i) Doubly robust inverse probability weighting method used for estimating standard errors (Sant'Anna & Zhao, 2020) (ii) ** p<0.05 (iii) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, if we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure A4.1. ATT – Robot adoption on reshoring index (excluding firms that abandon robot use).



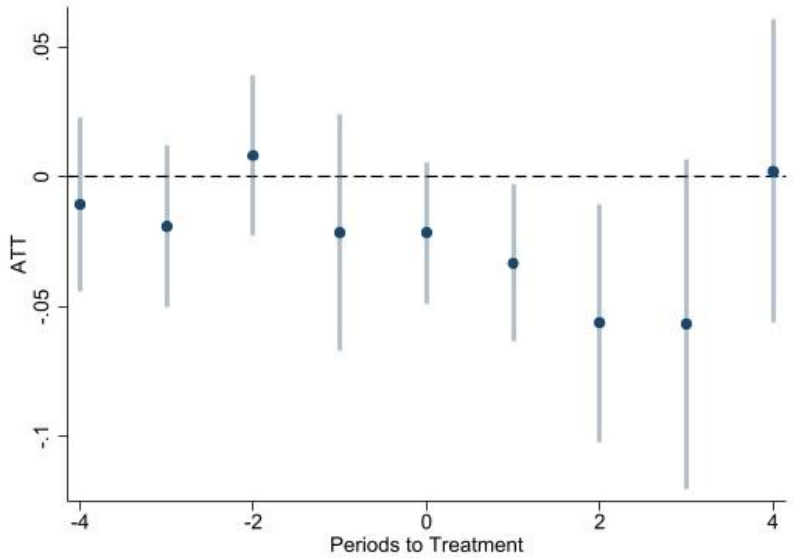

Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Table A4.4. Does robot adoption lead to reshoring? Importing intermediates from developed or developing countries. – Staggered DiD excluding firms that abandon robot use (ATT).

| | Importing intermediates from developed countries | Importing intermediates from developing countries |
|---|---|---|
| | (1) | (2) |
| | II/Y | II/Y |
| Robots | -0.037** | 0.031 |
| | (0.016) | (0.021) |
| Observations | 11,020 | 11,024 |
| Pretend test | 0.005 | -0.001 |
| | (0.010) | (0.005) |

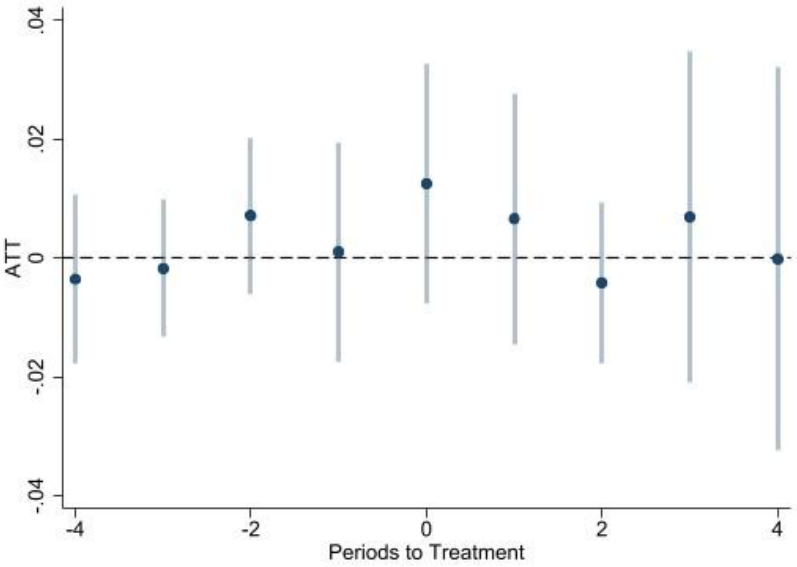
Notes: (i) Doubly robust inverse probability weighting method used for estimating standard errors (Sant'Anna & Zhao, 2020) (ii) ** p<0.05 (iii) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, if we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure A4.2. ATT – Robot adoption on reshoring index (importing intermediates from developed countries – excluding firms that abandon robot use).




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Figure A4.3. ATT – Robot adoption on reshoring index (importing intermediates from developing countries – excluding firms that abandon robot use).




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Table A4.5. Does robot adoption lead to reshoring? Importing intermediates mainly from developed or mainly from developing countries. – TWFE.

| | Importing intermediates from developed countries | Importing intermediates from developing countries |
|---|---|---|
| | (1) II/Y | (2) II/Y |
| Robots | -0.021* | -0.054 |
| | (0.012) | (0.059) |
| Observations | 10,465 | 1,489 |

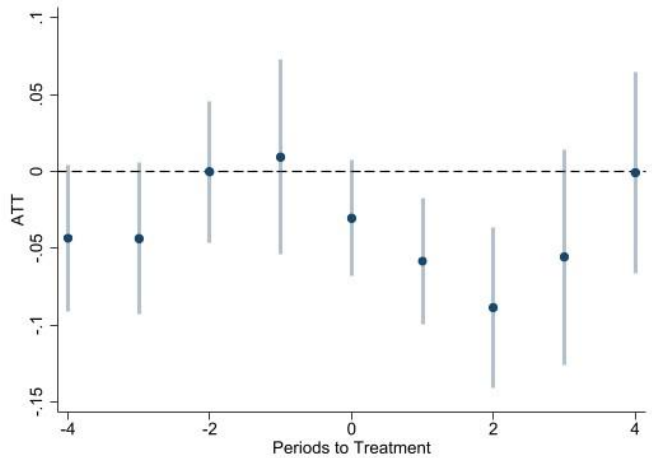
Notes: (i) Robust standard errors in parentheses (ii) * p<0.1 (iii) Clustered by firm (iv) All regressions include firm, industry and year fixed effects.

Table A4.6. Does robot adoption lead to reshoring? Importing intermediates mainly from developed or mainly from developing countries. – Staggered DiD (ATT).

| | Importing intermediates from developed countries | Importing intermediates from developing countries |
|---|---|---|
| | (1) II/Y | (2) II/Y |
| Robots | -0.059*** | -0.071 |
| | (0.020) | (0.077) |
| Observations | 5,980 | 948 |
| Pretend test | -0.005 | -0.075 |
| | (0.017) | (0.048) |

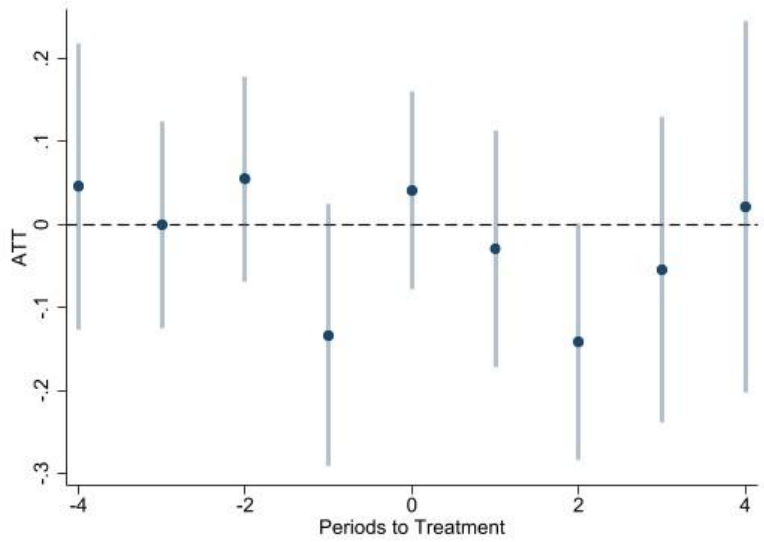
Notes: (i) Doubly robust inverse probability weighting method used for estimating standard errors (Sant'Anna & Zhao, 2020) (ii) *** p<0.01 (iii) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, if we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure A4.4. ATT – Robot adoption on reshoring index (firms importing intermediates mainly from developed countries).




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Figure A4.5. ATT – Robot adoption on reshoring index (firms importing intermediates mainly from developing countries).



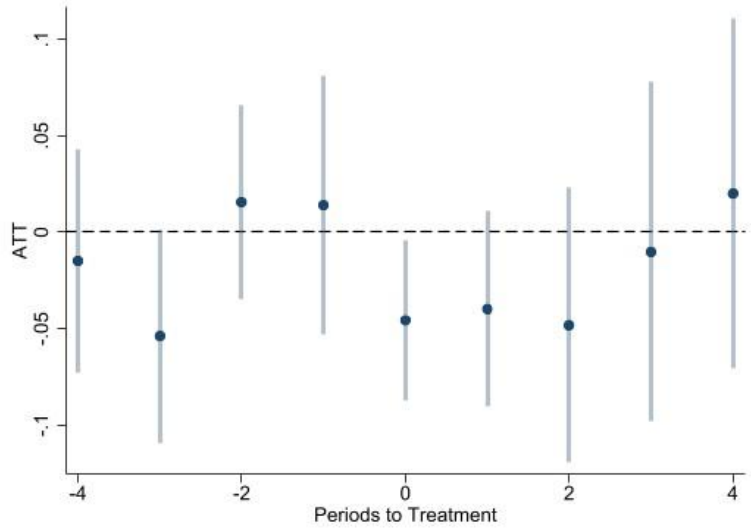

Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Table A4.7. Effect on the decomposition of the reshoring index – Staggered DiD excluding firms that abandon robot use (ATT).

| | (1)<br>II/TI | (2)<br>TI/Y |
|---|---|---|
| Robots | -0.043*<br>(0.024) | -0.037**<br>(0.014) |
| Observations | 11,230 | 10,966 |
| Pretend test | 0.002<br>(0.016) | -0.005<br>(0.003) |

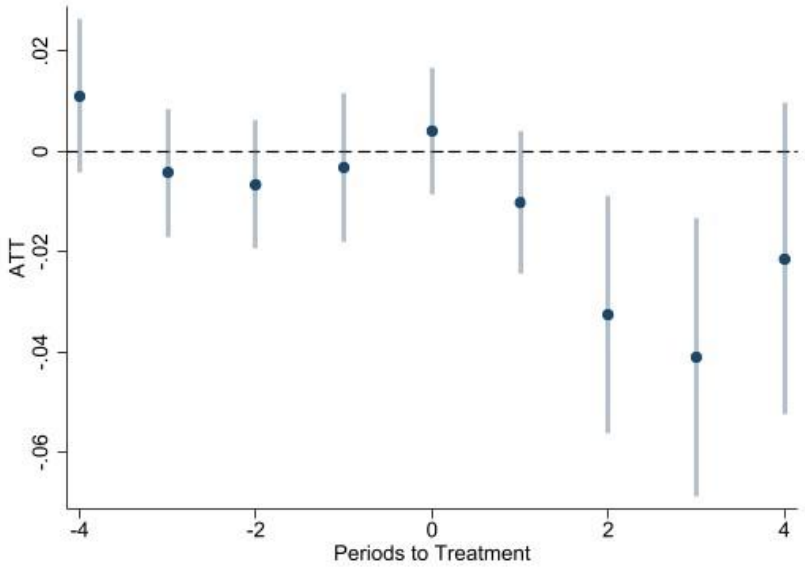
Notes: (i) Doubly robust inverse probability weighting method used for estimating standard errors (Sant'Anna & Zhao, 2020) (ii) ** p<0.05, * p<0.1 (iii) The pretrend test tests if all the pre-treatment effects are all equal to 0. Thus, if we do not reject the null, we can confirm that there were parallel trends prior to the treatment.

Figure A4.6. ATT – Robot adoption on II/TI excluding firms that abandon robot use.




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Figure A4.7. ATT – Robot adoption on TI/Y excluding firms that abandon robot use.




Note: The period t = 0 corresponds to the first year the firm adopts a robot. The bars are 90% confidence intervals for each yearly estimated effect (dot).

Table A4.8. Effect of robot adoption on TFP and sales.

| | (1)<br>TFP | (2)<br>Sales |
|---|---|---|
| $ROBOT_{i,t}$ | 0.033** | 0.067** |
| | (0.016) | (0.028) |
| Constant | 11.705*** | 15.440*** |
| | (0.002) | (0.004) |
| Observations | 12,164 | 12,252 |

Note: (i) Robust standard errors clustered by firm in parentheses (ii)*** p<0.01, ** p<0.05 (iii) All regressions include firm, industry and year fixed effects (iv) Sales are expressed in logarithms.

Table A4.9. Effect of robot adoption and TFP on the Reshoring Index, II and TI.

| | Total | | | Developed | | Developing | |
|---|---|---|---|---|---|---|---|
| | (1)<br>Reshoring Index | (2)<br>II | (3)<br>TI | (4)<br>Reshoring Index | (5)<br>II | (6)<br>Reshoring Index | (7)<br>II |
| $ROBOT_{i,t}$ | -0.023** | -0.559** | -0.013* | -0.026* | -0.529* | 0.003 | -0.230 |
| | (0.011) | (0.274) | (0.008) | (0.015) | (0.281) | (0.013) | (0.226) |
| $TFP_{i,t}$ | 0.083*** | 1.988*** | 1.491*** | 0.137*** | 3.002*** | 0.025*** | 0.719*** |
| | (0.012) | (0.291) | (0.015) | (0.020) | (0.335) | (0.008) | (0.186) |
| Constant | -0.761*** | -16.900*** | -2.644*** | -1.357*** | -26.595*** | -0.240*** | -0.240*** |
| | (0.140) | (3.411) | (0.170) | (0.251) | (4.131) | (0.085) | (0.085) |
| Observations | 12,164 | 12,164 | 12,164 | 6,738 | 6,738 | 5,242 | 5,242 |

Note: (i) Robust standard errors clustered by firm in parentheses (ii)*** p<0.01, ** p<0.05, * p<0.1 (iii) All regressions include firm, industry and year fixed effects. (iv) Intermediates Imported (II) and Total Intermediates (TI) are expressed in logarithms.

# Conclusions

Internationalisation strategies, and particularly Global Value Chains (GVCs) engagement can be highly beneficial for firms and economies. In this Thesis, we have studied how these internationalisation activities can help mitigate some of the main concerns in an economy, specifically focusing on Spain, i.e. unemployment and misallocation of production factors. Moreover, we have acknowledged the increasing presence of developing countries, and especially Sub-Saharan Africa countries, in the international value chains. Furthermore, we have also analysed how this engagement can be beneficial for them. Finally, we aimed at contributing to the current debate around the increase of new technologies and its potential impact on firms' internationalisation strategies. Next, we will wrap up the results from each chapter and the thesis will conclude with the policy recommendations we can retrieve from this study.

In Chapter 1, we find that exporter SMEs not only exhibit a higher level of employment than non-exporters, but they can also mitigate some of the employment losses that occur during a recessionary period that primarily affects domestic demand. This compensation acts in favour of permanent workers, meaning that the ratio of permanent to temporary workers increases during these recessive periods. Thus, exporting SMEs show greater resilience in terms of employment when affected by a recession than non-exporters. In addition, SMEs employ the export strategy as a means to survive and overcome periods of downturn in their domestic sales. In relation to this last point, we throw new empirical evidence on the "venting out" hypothesis (de Lucio et al., 2019; Almunia et al., 2021; Mañez et al., 2022). Finally, but very importantly, we also confirm the theoretical prediction in Almunia et al. (2021): those firms with the highest capacity utilisation have the greatest incentives to export when domestic demand falls.

In Chapter 2, applying Petrin and Sivadasan (2013)'s methodology to study misallocation of production factors from a firm-level point of view, we find that firms' participation in GVCs helps alleviate misallocation of intermediates. Hence, we show a source of allocative efficiency of intermediate inputs that can help us understand the evolution of Spanish TFP and be useful in efforts to improve it.

In Chapter 3, our results show that several factors in the business environment affect firms' participation in GVCs in Sub-Saharan Africa. We find that good infrastructure, strict fiscal control possibly signalling quality of institutions and security to prevent crime are conducive to participation. In contrast, difficult access to finance, the existence of an informal sector or high trade costs discourage participation. In terms of outcomes, Sub-Saharan African firms participating in GVCs enjoy superior innovation performance (both in terms of product upgrading and efficiency gains), higher productivity, pay higher wages and generate more employment.

In Chapter 4, we find that the use of robots in Spain leads to reshoring. However, robotisation leads to reshoring from developed countries, albeit for a limited duration. This suggests that foreign suppliers of intermediate inputs in these countries require a certain amount of time to adapt and invest in robotisation themselves. This adaptation process entails acquiring the necessary technology and expertise to effectively integrate robotics into their operations. On the other hand, there is no statistically significant reshoring from developing countries. This can be attributed to the fact that efficiency gains derived from robotics have not yet fully offset the cost differential between developed and developing countries, primarily driven by wage disparities. Furthermore, developing countries may have implemented measures to decrease wages in order to regain competitiveness in the global market. Finally, this robot-induced reshoring from developed countries is driven by the substitution of foreign sourcing with firms' internal

production. This supports the conclusion of the Chapter that reshoring contributes to increase firm employment. However, the positive effect on employment is somewhat diminished when reshoring is accompanied by robot adoption, as robots are likely involved in the production of a portion of the reshored goods within the firm.

Therefore, from the results of the Thesis we can retrieve several policy recommendations and conclusions. Firstly, with the first two chapters we provide solutions to mitigate job losses and misallocation for Spain. In Chapter 1, we align with the European needs of boosting SMEs performance. Interreg Europe presents in its agenda the necessity of implementing better policies in order to boost and support SMEs, since the competitiveness of these firms is at the forefront of their objectives (Interreg Europe, 2021). In order to achieve this increase in competitiveness, the Horizon 2030 of the European Commission also highlights the necessity of promoting the internationalisation of SMEs (Bichisao et al., 2019). Hence, our chapter sheds light on how this internationalisation of SMEs, more precisely through exporting, can help offset the shocks on employment suffered during downturns, gaining this way in competitiveness.

On the other hand, in Chapter 2, we unravel one source of reduction of intermediates misallocation, i.e. GVCs. In this line, policy makers should always be interested in understanding how to enhance TFP due to its implications for economic growth. However, it is of special interest for Spain because productivity is one of the structural problems of the Spanish economy (Fundación BBVA and Ivie, 2019). Hence, this study contributes for future policies by disentangling one of the factors behind the decrease in misallocation, what can be used to boost TFP. Also, as a counterpoint, trade policies should take into account that GVC engagement contributes to the reduction of misallocation. Therefore, a restriction to the functioning of GVCs should be taken with

caution, since it may have a deterrent effect on the efficient allocation of resources, and thus on TFP and output growth. In other words, the implications of GVC engagement on misallocation should be carefully considered when designing or modifying trade policies. This is of particular importance in light of the potential rise in protectionist policies that could hinder the functioning of GVCs.

In Chapter 3, we elucidate the determinants of GVC participation for firms in Sub-Saharan Africa. Likewise, we identify the significant benefits that firms can derive from this engagement. Hence, policymakers should consider this factor, as the participation of firms in Sub-Saharan Africa in GVCs can contribute to their growth, development, and active involvement in the international arena. However, we acknowledge a result in this chapter: workers' skill intensity has a negative effect on the likelihood of participating in GVCs. So far, Sub-Saharan countries have the comparative advantage of being endowed with abundant low-cost unskilled labour, which has been attractive for labour-intensive manufacturing activities. However, as Rodrik (2018) highlights, GVCs are increasingly intensive in new technologies, which may pose a threat to these countries. The lack of skills required to handle these technologies may diminish their comparative advantage, as several authors highlight the importance of skilled labour (Hollweg, 2019) or even automation (Stapleton, 2019) in GVCs. However, we shed light on this question in Chapter 4.

Chapter 4 shows that the increase in robotisation in a developed country such as Spain, does not lead to reshoring from developing countries. Thus, our findings may offer some relief for developing countries regarding the impact of robotisation. Nevertheless, we cannot determine from this study whether this is due to a downward adjustment of their wages in response to competitiveness loss. Nonetheless, if the adoption of robotisation in one developed country prompts other developed countries to follow suit

and regain competitiveness, it could result in an uncertain escalation of robotisation. Furthermore, our study highlights that reshoring resulting from robotisation in a developed country can occur through the substitution of foreign suppliers with in-house production. This reshoring can contribute to firms' employment and plays a critical role in the ongoing debate concerning the trade-off between robotisation and employment.

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