Universidad de Las Palmas de Gran Canaria

Departamento de Métodos Cuantitativos en Economía y Gestión

Análisis econométrico de la gestión financiera empresarial en Ecuador

Tesis Doctoral

José Salvador Cortés García

Las Palmas de Gran Canaria, 2024

Director: Dr. Jorge V. Pérez Rodríguez

Universidad de Las Palmas de Gran Canaria

Acta de autorización

UNIVERSIDAD DE LAS PALMAS DE GRAN CANARIA

ESCUELA DE DOCTORADO

Programa de doctorado en **Turismo, Economía y Gestión**.

Título de la Tesis **"Análisis econométrico de la gestión financiera empresarial en Ecuador"**.

Tesis Doctoral presentada por **D. José Salvador Cortés García**.

Dirigida por el Dr. **D. Jorge Vicente Pérez Rodríguez**

Las Palmas de Gran Canaria, a de de 2024

El/la Director/a, El/la Codirector/a El/la Doctorando/a,

(firma) (firma) (firma)

Agradecimientos

El viaje del conocimiento no tiene un punto final, sino que se configura como una búsqueda constante de la verdad, la comprensión y la transformación social, a través de un espíritu crítico que conduzca a un conocimiento más justo, inclusivo y equitativo.

Expreso mi sincero agradecimiento a la Universidad Técnica Particular de Loja por haberme brindado la oportunidad de cursar el Doctorado en Turismo, Economía y Gestión. Mi gratitud por siempre por el invaluable apoyo recibido por parte de las autoridades, profesores, personal administrativo y de apoyo, quienes con profesionalismo facilitaron mi desarrollo académico y personal.

Agradezco a la Universidad de Las Palmas de Gran Canaria por haberme aceptado en su programa de doctorado y por la oportunidad de realizar estancias de investigación en sus instalaciones. Agradezco la calidez y el generoso apoyo recibido por parte de la comunidad universitaria, quienes me brindaron un espacio de aprendizaje enriquecedor y me permitieron establecer valiosas relaciones profesionales y personales.

De manera especial a mi director de tesis, Jorge V. Pérez-Rodríguez, por su invaluable guía, paciencia y apoyo durante todo el proceso de investigación. Agradezco su generosa dedicación y aportes, así como su confianza en mi trabajo. Particularmente, agradezco por sus consejos y ejemplo de perseverancia, los llevaré siempre conmigo.

Mi principal agradecimiento lo dedico a mi esposa y mis hijos, a quienes amo profundamente. A mi esposa Clara, que me acompañó en esta experiencia académica con paciencia, pero también transmitiéndome entereza en momentos cruciales. A Juan Andrés, que con su espíritu decidido a lograr sus metas y enfrentar los retos de la vida, me regaló parte de su valioso tiempo y con ello me dió impulsos para continuar en este proyecto académico. A Salvador Alejandro, el menor de la familia, que en incontables ocasiones aparcó su deseo de invitarme a compartir tiempo en sus juegos, permitiéndome continuar en el proyecto de investigación. De mi esposa y mis hijos también aprendí el valor del tiempo,

que con generosidad incondicional me han brindado estos años dedicados al doctorado. Pondré todo mi esfuerzo para compensarlos por su inmensurable comprensión, paciencia, y cariño.

Resumen

El objetivo de la presente Tesis Doctoral ha sido analizar el comportamiento de la gestión financiera en Ecuador mediante el estudio de compañías del sector productivo y de la banca privada. El tema se aborda desde una temporalidad acotada en el periodo 2007-2017. Las principales características de este periodo son la continuidad de una misma administración pública y algunas reformas legales aplicables tanto al sector empresarial como al sector bancario. Desde ese contexto, el estudio se desarrolla desde tres objetivos específicos. El primero, identificar los determinantes que afectan a la composición de la estructura de capital del sector empresarial, diferenciando entre compañías listadas y no listadas en la bolsa de valores ecuatoriana. El segundo, estudiar la eficiencia de los bancos privados ecuatorianos, considerando múltiples productos y factores de producción (inputs), así como varios determinantes que expliquen la ineficiencia que es variable en el tiempo. Y el tercero, analizar la evolución de la eficiencia del sector hotelero, específicamente, a partir del uso de tecnologías de producción en el marco de modelos no paramétricos que emplean varios productos y factores de producción, así como analizando su nivel de desempeño por regiones ecuatorianas.

Determinantes de la estructura de capital

La relevancia de la estructura de capital, tema que se sigue estudiando en la actualidad, radica en la importancia del acopio de fondos para financiar las inversiones. Concretamente, es de interés para las compañías establecer una relación adecuada entre el financiamiento por deuda y el financiamiento patrimonial. Esta adecuación, por lo general responde a factores que influyen tanto en la disposición de proveedores externos de fondos como en la actitud de los inversores patrimoniales, a partir de las expectativas de retornos futuros en cualquier compañía con fines lucrativos. Por tanto, se asume que ambos grupos de financistas actúan a partir de determinantes específicos que están asociados con la capacidad de la compañía para generar flujos de efectivo libres, disponibles para los inversores.

El origen del estudio de la estructura de capital bajo enfoques teóricos como la irrelevancia, compensación, orden jerárquico, costos de agencia, o señalización, se basó en

la identificación de sus determinantes en empresas listadas en mercados de valores, debido a la disponibilidad de información financiera pública. Sin embargo, el interés científico en este tema, dada su importancia en el desarrollo empresarial, ha propiciado una expansión de este enfoque investigativo hacia el conjunto de empresas en general, listadas o no listadas. Particularmente, este fenómeno se da en las últimas dos décadas en las que se han generado a nivel global más bases de datos públicas con indicadores financieros empresariales.

La literatura preexistente demuestra que los resultados varían entre regiones o países. Los estudios de compañías que operan en entornos competitivos afines suelen identificar variables similares correlacionadas con la estructura de capital, lo que da consistencia a las teorías empleadas (Rajan & Zingales, 1995). Desde otro enfoque, las características estructurales y administrativas de cada compañía generan variaciones significativas en los resultados. Además, los factores económicos e institucionales, específicos de cada país, pueden influenciar las decisiones de negocios relacionadas con la estructura de capital (Booth et al., 2001; Wald, 1999).

Siguiendo el primer objetivo de esta Tesis Doctoral, la estructura de capital y sus determinantes fueron estudiados sobre la formulación de paneles de datos no balanceados. En general, los datos fueron tomados de los estados financieros anuales publicados por la Superintendencia de Compañías, Valores y Seguros de Ecuador. Con ellos, conformamos una muestra de 292 compañías listadas en el mercado de valores ecuatoriano, y una muestra de 10,572 no listadas, que fueron tratadas metodológicamente por separado para contrastar los resultados.

El conjunto de factores determinantes de la estructura de capital utilizados son los clásicos empleados en la literatura empírica sobre este tipo de estudios, como son la rentabilidad, tamaño, crecimiento, tangibilidad, liquidez, dividendos, escudo fiscal del gasto de capital, edad, y sector productivo. Estos determinantes han sido investigados tradicionalmente para probar teorías relevantes de la estructura de capital, como la teoría de la compensación (*Trade-off Theory*) y la teoría del orden jerárquico (*Pecking Order Theory*). Estas teorías asumen que el endeudamiento externo en las compañías puede ser útil para

incrementar la rentabilidad empresarial, cuando la deuda sustituye parte del capital accionario. La medición de los efectos de los determinantes en la estructura de capital se hizo mediante un modelo dinámico de datos de panel basado en el ajuste del apalancamiento objetivo (utilizando la hipótesis de ajuste parcial).

Partiendo del modelo dinámico general de datos de panel basado en un proceso autorregresivo de orden *p* con variables estrictamente exógenas y endógenas como regresores, se usaron dos estimadores de tipo GMM. Uno es el desarrollado por Arellano y Bond (1991) para conjuntos de datos con numerosos paneles y pocos períodos. Este estimador puede generar un rendimiento poco satisfactorio cuando los parámetros autorregresivos o la relación entre la varianza del efecto a nivel de panel y la del error idiosincrático, fuesen elevados. El otro estimador considerado es el de Blundell y Bond (1998) con el cual se obtiene una estimación más eficiente de los parámetros.

Para validar la estimación del modelo dinámico de datos panel, primero se estudió la existencia de raíces unitarias en los datos. En este sentido, se aplicó la prueba de raíz unitaria de panel de tipo Fisher, que supone que no hay dependencia cruzada entre empresas. Los resultados de la prueba indican que debe rechazarse la hipótesis nula de que todos los paneles contienen raíces unitarias. En consecuencia, algunos paneles son estacionarios, por tanto, el modelo dinámico de datos de panel propuesto es factible.

Los principales resultados de este estudio indican que las empresas necesitan tiempo para ajustar sus estructuras de capital a los cambios en las condiciones económicas. Los modelos de panel dinámicos generados con base en los métodos de datos en panel utilizados muestran que las empresas de este estudio utilizan un mecanismo de ajuste parcial para determinar su estructura de capital. Así, el nivel de apalancamiento observado en un periodo actual depende del empleado en el periodo anterior (persistencia). Además, el efecto del apalancamiento retardado es más pronunciado a corto plazo que a largo plazo.

Respecto a los determinantes de la estructura de capital, tanto las empresas que cotizan en bolsa como las que no lo hacen están influenciadas por factores explicativos tradicionales, como el tamaño, la rentabilidad, la tangibilidad, el crecimiento y el escudo fiscal sin deuda.

Otros factores, como la liquidez y los dividendos, no son significativos o no son representativos. En general, tanto para las empresas que cotizan en bolsa como para las que no, los efectos de estas variables sobre la estructura del capital se ajustan a la teoría del *pecking order*, con excepción de la variable tamaño, cuyo efecto se alinea con la teoría del *trade-off*. Respecto a las variables de control, el sector industrial influye en la estructura del capital de los dos grupos, mientras que la edad no es significativa para las empresas cotizadas, y si para las que no cotizan en bolsa.

Los resultados indican que en la estructura de capital el capital propio predomina sobre el apalancamiento a largo plazo entre las empresas ecuatorianas, lo que podría obstaculizar las oportunidades de crecimiento basadas en la financiación externa a largo plazo. Esto pone de relieve la importancia de comprender los aspectos de la estructura de capital en Ecuador, en particular las diferencias entre las empresas que cotizan y las que no cotizan en bolsa, lo que ofrece información valiosa para inversores, financieros y funcionarios públicos.

Es esencial reconocer dos limitaciones en este estudio: en primer lugar, el período incompleto de información para determinadas empresas de la muestra, unido a las dificultades para acceder a datos adicionales sobre posibles determinantes de la estructura de capital. En segundo lugar, las diferencias contextuales únicas entre diversos sectores industriales. Abordar estas limitaciones facilitaría una comprensión más específica de las cuestiones examinadas, atenuando las generalizaciones relativas a las condiciones de acceso a la financiación y los planteamientos de las empresas en materia de estructura del capital.

En resumen, mejorar la sinergia entre los sectores productivo y financiero es imperativo en el panorama empresarial de Ecuador. Reorientar el enfoque de la financiación a corto plazo hacia iniciativas estratégicas de estructura de capital podría ser la clave para fomentar un desarrollo acelerado dentro del sector empresarial del país.

Eficiencia de la banca privada

La eficiencia bancaria es un tema de vital trascendencia, puesto que por sus propias características la banca tiene un rol preponderante en el desarrollo del sistema económico y financiero nacional. Por tanto, la sostenibilidad de los bancos dependerá de la eficiencia con

la que sean gestionados sus recursos operativos para generar producción y rentabilidad. Sin embargo, la gestión bancaria está sometida a regulaciones que condicionan diversos aspectos como las tasas de interés activas y pasivas, así como a un conjunto de indicadores financieros que deben mantenerse en rangos o niveles predeterminados. En ese marco regulatorio, la gestión bancaria debe implementar estrategias que le permitan alcanzar sus objetivos financieros, donde cada banco mantenga niveles de eficiencia que le conduzca a la sostenibilidad y alejarse del riesgo de quiebra.

Con relación al segundo objetivo de esta tesis, el estudio de la banca privada comercial ecuatoriana se desarrolla a partir la información de los estados financieros anualizados de 18 bancos comerciales privados por el periodo 2007-2017. En este contexto, estudiamos la eficiencia desde distintos enfoques metodológicos no paramétricos, descritos a continuación.

Análisis de frontera estocástica (SFA)

Con este método estimamos la eficiencia considerado múltiples inputs y outputs, varios factores explicativos de la ineficiencia, heterogeneidad tecnológica no observada y eficiencia variable en el tiempo. Para ello, se utiliza un modelo de frontera estocástica con función distancia orientada hacia el output en un marco bayesiano y se considera el enfoque de rentabilidad.

La heterogeneidad en la producción o en los costes es una característica importante de las empresas, que puede influir en su eficiencia. Las teorías de gestión estratégica, como la visión de la empresa basada en los recursos (RBV) (por ejemplo, Barney, 1991; Conner, 1991; Peteraf, 1993; Wernerfelt, 1984), destacan el papel de los recursos heterogéneos entre las empresas para lograr ventajas competitivas. Esta heterogeneidad puede ser causada por factores como el tamaño, la propiedad, la tecnología, las características de la empresa y la capacidad de los directivos, entre otros factores descritos en la literatura.

La especificación general de nuestra función de distancia de producción orientada hacia el output se basa en el modelo de frontera de producción estocástica de tipo translog, en la que modelizamos la heterogeneidad tecnológica no observada y la ineficiencia técnica

variable en el tiempo considerando que la media condicional de la ineficiencia depende de otros factores bancarios y económicos (covariables). Posteriormente, estimamos nuestro modelo de datos de panel utilizando un modelo de parámetros aleatorios en un enfoque bayesiano.

En el modelo utilizamos los gastos de explotación, los costes de personal y los gastos por intereses como inputs, y consideramos la cantidad total de préstamos, depósitos e ingresos (intereses + comisiones) como outputs. Además, consideramos los préstamos morosos (NPL) como un output indeseable siguiendo la investigación bancaria reciente. También incluimos el capital financiero como covariable en la especificación de la frontera, así como las tendencias temporales lineal y cuadrática para representar el progreso tecnológico. Como factores ambientales que explican la ineficiencia variable en el tiempo, consideramos algunos determinantes: número de años en el negocio, tamaño, rentabilidad operativa, propiedad nacional o extranjera, y nivel de reservas bancarias.

En general, los resultados muestran evidencia de heterogeneidad no observada entre bancos e ineficiencias variables en el tiempo. Además, las puntuaciones de eficiencia variables en el tiempo son elevadas y estables, y un factor que explica significativamente la ineficiencia, pero de forma negativa, es la propiedad extranjera, pero no factores internos como la rentabilidad operativa y las reservas obligatorias impuestas por el Banco Central de Ecuador. Por último, los rendimientos a escala estimados muestran una bimodalidad que indica la existencia de dos grupos de bancos asociados con rendimientos a escala decrecientes y constantes.

Este enfoque tiene un gran potencial para ofrecer a los directivos de los bancos información valiosa sobre las implicaciones a corto plazo en el sector. Los gerentes de los bancos desempeñan un papel fundamental en la eficiencia de las operaciones, ya que requieren competencias diversas como la relación con el cliente, la gestión de la marca, la supervisión de los ingresos y el presupuesto, entre otras. Los resultados indican que la eficiencia varía con el tiempo, lo que obliga a los directivos de los bancos ecuatorianos a adaptarse a los cambios años tras año. En particular, los directivos de los bancos ecuatorianos

deberían mejorar sus prácticas de gestión en comparación con sus homólogos extranjeros. Aunque los bancos más grandes tienden a aumentar la concentración del mercado, sus resultados financieros fueron inferiores a los de los bancos medianos a la conclusión del estudio. Esto subraya la importancia de analizar los gastos operativos y los objetivos de ingresos por tipo de producto o servicio. Sin embargo, nuestros resultados no demuestran que algunos factores del entorno, como los requisitos de reservas bancarias, la antigüedad y la rentabilidad operativa, influyen en la eficiencia.

Este estudio reconoce algunas limitaciones. Por ejemplo, el tamaño de la muestra de bancos es relativamente bajo a pesar de un número adecuado de períodos. Por lo tanto, futuros estudios podrían abarcar otras instituciones financieras ecuatorianas, incluidas las cooperativas de ahorro y crédito, para proporcionar un análisis más exhaustivo, teniendo en cuenta las nuevas normativas destinadas a mejorar la competitividad de la banca. Adicionalmente, podrían introducirse otros enfoques econométricos que utilicen el modelo de parámetros aleatorios en el marco bayesiano, asumiendo otras distribuciones para los términos de ineficiencia, como la truncada-normal, que permite modelizar la media condicional a lo largo del tiempo en función de las covariables. Además, la investigación futura podría desarrollar modelos que separen la eficiencia bancaria entre las partes transitorias (no sistemáticas) y persistentes (sistemáticas), para evitar la posible estimación sesgada de la ineficiencia global, especialmente si la ineficiencia persistente y la heterogeneidad no observada (ambas o no) están presentes (Colombi et al., 2014).

Análisis envolvente de datos (DEA)

Este estudio se enmarca en el contexto de mayor regulación aplicada a la banca en Ecuador luego de la crisis de finales del siglo pasado que condujo a la dolarización de la economía. Particularmente, en el período 2007-2017 se acentuaron algunas normas como la regulación de tasas de interés activas y pasivas, el encaje legal, la mantención de 10% de la cartera de créditos, así como la mantención de niveles adecuados de provisiones para cuentas incobrables (*loan loss provisions,* LLP), entre otras medidas de control. Consecuentemente, este estudio pone en relieve cómo determinados factores reguladores afectan a la eficiencia

bancaria, en tanto que el objetivo de estas normas es impulsar la sostenibilidad del sistema bancario.

Con metodología DEA analizamos la eficiencia del mismo conjunto de bancos, utilizando múltiples inputs y outputs. DEA utiliza medidas radiales y no radiales para evaluar la eficiencia de las unidades a evaluar (DMUs) (Ashrafi et al., 2013). Los modelos DEA radiales clásicos como CCR (Charnes et al., 1978) o BCC (Banker et al., 1984) suponen que hay un cambio proporcional de los inputs y outputs, pero no tienen en cuenta las holguras en las puntuaciones de eficiencia y pueden presentar desviaciones significativas (Deng et al., 2020). Del otro lado, las medidas DEA no radiales, como SBM (*slacks based measure*), tienen en cuenta las holguras de cada entrada y salida y permiten las variaciones tanto de los inputs como de los outputs, que no son proporcionales. SBM permite la separación de outputs buenos y outputs indeseables o malos, utilizando la tecnología de rendimientos variables a escala (*variable returns to scale,* VRS) (Tone, 2003).

Para la estimación de las eficiencias, utilizamos una metodología enfocada en un procedimiento en dos etapas. En la primera etapa, aplicamos un modelo de medida basada en la holgura (SBM) que trata los resultados indeseables, asumiendo VRS, el cual contrastamos con un modelo DEA-BCC y con los respectivos Bootstrap tanto del modelo SBM como del modelo DEA-BCC. En la segunda etapa, evaluamos el efecto en la eficiencia bancaria de algunos factores económicos utilizados en estudios previos.

En la primera etapa, los inputs utilizados en los modelos de eficiencia son los gastos de operación y gastos de personal, mientras que los outputs son el margen bruto, el total de depósitos, el total de la cartera de créditos. Particularmente, evaluamos los efectos de las provisiones para insolvencias (LLP) y los préstamos morosos (*non-performing loans,* NPL) sobre la ineficiencia de los bancos utilizándolos como outputs no deseables y midiendo por separado su impacto.

En la segunda etapa, evaluamos los efectos de algunas covariables en las eficiencias obtenidas con los modelos SBM que contienen los outputs indeseables LLP y NPL. Para ello, estimamos los efectos a partir de una regresión Tobit censurada utilizando la máxima

verosimilitud. Los determinantes o covariables utilizados son la tendencia lineal en el tiempo, los años en el negocio o edad, los beneficios brutos de la cartera, la proporción de la cartera comercial, el rendimiento sobre los activos (*return on assets*, ROA), la cuota de mercado, el escudo fiscal de las depreciaciones (*non-debt tax shield*, NDTS), la tasa de depósitos requerida por el Banco Central, la ratio de préstamos sobre depósitos. Además, incluimos un par de variables categóricas: bancos listados, y tipo de propiedad.

Los principales resultados muestran varias facetas. En primer lugar, los bancos más grandes tienden a ser más eficientes que los medianos y pequeños. En segundo lugar, la utilización de los préstamos morosos como output indeseable representa mayor ineficiencia basada en las holguras (SBM). Y, en tercer lugar, el uso de LLP sobreestima la eficiencia de los bancos cuando se utiliza como output indeseable. Respecto de los determinantes significativos en uno o los dos modelos evaluados, la edad de los bancos y el escudo fiscal por depreciaciones influyen negativamente en la eficiencia, mientras que la cuota de mercado y la tasa sobre depósitos lo hacen positivamente.

En general, los resultados sugieren una influencia generalmente positiva de la normativa bancaria ecuatoriana sobre la eficiencia. Sin embargo, el requisito de reserva de morosidad parece contraproducente, ya que afecta negativamente a la eficiencia al aumentar las ratios de capital. Un hecho interesante es la tendencia positiva del ROA, que podría deberse a la misma regulación.

El estudio arroja tres conclusiones clave. En primer lugar, las regulaciones ecuatorianas parecen promover la profundización financiera mediante el control de los tipos de interés y mitigar los préstamos morosos a través de las reservas de capital. En segundo lugar, estas regulaciones impulsan a los bancos a adaptarse y mantener una elevada eficiencia. Por último, las instituciones menos eficientes pueden aprovechar los indicadores de rendimiento de sus homólogas para mejorar.

El estudio reconoce algunas limitaciones. La ampliación de la muestra para incluir otras instituciones financieras además de los bancos comerciales en el periodo analizado ofrece un valioso margen para futuras investigaciones. Además, la incorporación de variables

explicativas alternativas, como el riesgo de crédito y la liquidez, podría mejorar la comprensión de los determinantes de la eficiencia.

Eficiencia de la industria hotelera

El análisis de la eficiencia en la industria hotelera ecuatoriana es una tarea crucial para mejorar su competitividad y sostenibilidad a largo plazo. Comprender los niveles de eficiencia permite identificar áreas de mejora en los procesos operativos y la gestión de recursos, optimizar la utilización de los recursos disponibles, reducir costos y aumentar la rentabilidad de los hoteles, y con ello, mejorar la calidad de los servicios y la satisfacción de los clientes. En un contexto de alta competencia global, la eficiencia productiva se convierte en un factor determinante para el éxito de la industria hotelera ecuatoriana. Sin embargo, la entrada en vigor de normas laborales y contables puede condicionar la competitividad y eficiencia en un sector como el hotelero, caracterizado financieramente por requerir niveles altos de inversiones y gastos fijos.

Para dar respuesta al tercer objetivo de esta tesis, analizamos la eficiencia sobre la formulación de un panel de datos no balanceado. Este aspecto es consecuencia de las dificultades de las compañías para sostenerse en el tiempo en un mercado de alta competencia. En general, los datos utilizados para medir la eficiencia fueron tomados de los estados financieros anuales publicados por la Superintendencia de Compañías, Valores y Seguros de Ecuador, por el periodo 2007 a 2017. Con ellos, conformamos una muestra de 93 compañías de alojamiento que operan en cuatro regiones de Ecuador: Costa, Sierra, Amazonía y Galápagos.

Este estudio usa un procedimiento de dos etapas para evaluar los determinantes de la eficiencia operativa de la industria de alojamiento en Ecuador. En la primera etapa hemos estimado las eficiencias basado en un enfoque de programación matemática no paramétrica para la estimación de fronteras con métodos radiales (DEA) y no radiales (SBM). Estas herramientas matemáticas permiten evaluar la eficiencia de un conjunto de empresas, tomando en cuenta sus diferentes características y recursos. Además, hemos utilizado el enfoque Bootstrap (bootstrap-DEA y bootstrap-SBM) para estimar de forma más precisa la

distribución desconocida de las puntuaciones de eficiencia, siguiendo la secuencia metodológica de Wang et al. (2020) a partir del procedimiento de Simar and Wilson (1998). Para esto, y con base en los datos disponibles, seleccionamos los siguientes inputs: el número de trabajadores, los gastos de mano de obra (coste de los salarios más prestaciones de los empleados), los gastos de material (incluye los gastos de equipamiento) y otros gastos, mientras que como output usamos los ingresos totales.

En la segunda etapa, analizamos el efecto de varios determinantes (covariables) sobre las eficiencias de los hoteles en Ecuador obtenidas en los diferentes modelos de la primera etapa. Para ello, aplicamos el procedimiento de Simar and Wilson's (2007) basado en la regresión truncada para los métodos DEA radiales, mientas que para los métodos SBM no radiales utilizamos la regresión censurada de Tobit. En ambos casos utilizamos la máxima verosimilitud y, en el caso del procedimiento de Simar y Wilson, utilizamos 2000 simulaciones bootstrap para cada puntuación de eficiencia.

Los determinantes utilizados representan distintos aspectos: características regulatorias, características de las compañías hoteleras (económicas y financieras), y variables de control. Respecto a las características regulatorias, consideramos la adopción en 2010 de las normas internacionales de información financiera (IFRS) y la reforma laboral que regula el tipo de contratación a partir del 2008. Entre las variables económico-financieras consideramos las siguientes: el rendimiento operativo representando la habilidad gerencial para utilidades basadas en los activos disponibles; la cuota de mercado que indica el porcentaje de ingresos obtenidos del total del mercado; el nivel de endeudamiento indicando el nivel de activos financiado con deuda; y la edad como variable representativa de la experiencia y la reputación de la marca. Otras variables categóricas utilizadas son: el tamaño (para identificar compañías ubicadas en el cuartil superior en relación al valor de sus activos); si los hoteles están listados, para diferenciar aquellas negociadas en bolsa de las no listadas en el mercado de valores; si el hotel es de capital extranjero (para diferenciar la compañías con capital extranjero); la categoría que representa el estatus de calidad de cada hotel; la estructura legal para clasificar las compañías por el tipo de figura asociativa; y, finalmente, la región y provincia que indican la ubicación regional y provincial de cada hotel.

Los principales resultados muestran que la industria de alojamiento ecuatoriana opera con una eficiencia global superior al 70% con tendencia a disminuir con el tiempo en el periodo analizado. Al contrastar los modelos, los hoteles ineficientes detectados con el modelo DEA se volvieron más ineficientes con el modelo SBM, por tanto, las eficiencias medidas con el modelo no radial fueron sistemáticamente inferiores a las del modelo radial. Desde otro punto de vista, las eficiencias globales en las regiones Amazonía y Galápagos superan a las obtenidas en la región Costa, que a su vez muestra mejor resultado comparada con la región Sierra. Por último, estudiando las ineficiencias generadas por los inputs, se observan puntuaciones globales más altas en el número de empleados y el coste de personal. Al analizar el comportamiento en el tiempo, es notorio que, en el año 2007, previo a la reforma laboral, las ineficiencias en los inputs son considerablemente menores a las obtenidas en años posteriores como el 2011.

Con relación a los determinantes de la eficiencia de los hoteles ecuatorianos, encontramos que los efectos correspondientes a las variables estadísticamente significativas tienden a ser consistentes en el conjunto de modelos planteados. Los factores que influyen positiva y significativamente en la eficiencia son: reforma laboral, periodo de crisis, rentabilidad operativa, cuota de mercado, tamaño, y hoteles listados en bolsa de valores. En sentido contrario, los factores que influyen negativa y significativamente son: adopción de normas internacionales de información financiera, y edad.

Los resultados nos guían a concluir que los gerentes de hoteles ecuatorianos pueden obtener valiosos conocimientos de este estudio para aumentar su eficiencia. Las consideraciones financieras incluyen alinear los objetivos de desempeño con la realidad financiera, optimizar la relación costo-ingreso y gestionar el apalancamiento de la deuda de manera estratégica. Respecto a las decisiones de recursos humanos, estas implican elegir modelos de contratación sostenibles y especializarse por segmento de mercado. En términos de competencia, podrían compartir conocimientos y formar *clusters* para mejorar la competitividad. Con relación a determinadas categorías, los hoteles más antiguos asumen mayores costos de mantenimiento y deben considerar la modernización. También, los

gerentes hoteleros pueden evaluar las ventajas de cotizar en bolsa, por ejemplo, beneficiarse de un acceso más fácil a fondos y acrecentar el prestigio de la compañía.

Finalmente, si bien existen limitaciones en la calidad de los datos y la composición de la muestra, la investigación futura que utilice encuestas e incorpore factores adicionales puede mejorar aún más la comprensión de la eficiencia hotelera en Ecuador. Al implementar estas recomendaciones y abordar las limitaciones, los hoteles pueden mejorar su eficiencia y seguir siendo competitivos.

Palabras clave: Estructura de capital, Teoría del *trade-off*, Teoría de *Pecking-order*, Pruebas de raíz unitaria, Datos dinámicos de panel, bancos, función de distancia de producción, modelo de frontera estocástica translog, efectos aleatorios, eficiencia, SBM, output indeseable, empresas de alojamiento, DEA, medida basada en holguras (SBM), bootstrap-DEA, bootstrap-SBM.

Abstract

This Doctoral Thesis aims to analyze financial management behavior in Ecuador by studying companies in the productive sector and private banking. The topic is approached from a limited time frame from 2007-2017. The main characteristics of this period are the continuity of the same public administration and some legal reforms applicable to both the business and banking sectors. In this context, the study is developed from three specific objectives. The first is to identify the determinants that affect the composition of the capital structure of the corporate sector, differentiating between companies listed and unlisted on the Ecuadorian stock exchange. The second is to study the efficiency of Ecuadorian private banks, considering multiple products and factors of production (inputs), as well as various determinants that explain the inefficiency, which is variable over time. The third is to analyze the evolution of the efficiency of the hotel sector, based explicitly on the use of production technologies in the framework of non-parametric models that use various products and production factors, as well as analyzing their level of performance by Ecuadorian regions.

Capital structure determinants

The relevance of capital structure, a subject still being studied today, lies in the importance of raising funds to finance investments. Specifically, it is in the interest of companies to establish an appropriate relationship between debt financing and equity financing. This adequacy generally responds to factors that influence both the willingness of external fund providers and the attitude of equity investors based on the expectations of future returns in any for-profit company. Therefore, it is assumed that both groups of financiers act on specific determinants associated with the company's ability to generate free cash flows available to investors.

The origin of the study of capital structure was based on the analysis of its behaviour in companies listed on stock markets due to the availability of public financial information. However, the scientific interest in this topic, given its importance in business development, has led to expanding this research approach to the set of companies in general, listed or

unlisted. This phenomenon has occurred in the last two decades, during which more databases with business financial indicators have been generated.

Pre-existing literature shows that results vary across regions or countries. Studies of companies operating in related competitive environments tend to identify similar variables correlated with capital structure, which gives consistency to the theories employed (Rajan & Zingales, 1995). From another approach, each company's structural and administrative characteristics generate significant variations in results. In addition, economic and institutional factors specific to each country can also influence business decisions related to capital structure (Booth et al., 2001; Wald, 1999).

Following the first objective of this Doctoral Thesis, the capital structure and its determinants were studied in the formulation of unbalanced panel data. The data were taken from the annual financial statements published by the Superintendence of Companies, Securities and Insurance of Ecuador. With them, we formed a sample of 292 companies listed in the Ecuadorian stock market and 10,572 unlisted companies, which were methodologically treated separately to contrast the results.

The set of determinants of capital structure used are the classic ones employed in the empirical literature on this type of study, such as profitability, size, growth, tangibility, liquidity, dividends, capital expenditure tax shield, age, and productive sector. These determinants have traditionally been investigated to test relevant capital structure theories, such as Trade-off Theory and Pecking Order Theory. These theories assume that external indebtedness in companies can help increase corporate profitability when debt replaces part of the equity capital. The effects of the determinants on capital structure were measured using a dynamic panel data model based on the target leverage adjustment (using the partial adjustment assumption).

Starting from the general dynamic panel data model based on a *p*-order autoregressive process with strictly exogenous and endogenous variables as regressors, two GMM-type estimators were used. One was developed by Arellano and Bond (1991) for data sets with many panels and few periods. This estimator can generate unsatisfactory performance when

the autoregressive parameters or the ratio between the variance of the panel-level effect and the idiosyncratic error are high. The other estimator considered is that of Blundell y Bond (1998), with which a more efficient estimation of the parameters is obtained.

We first studied the existence of unit roots in the data to validate the estimation of the dynamic panel data model. The Fisher-type panel unit root test, which assumes no cross-dependence between companies, was applied in this regard. The test results indicate that the null hypothesis that all panels contain unit roots should be rejected. Consequently, some panels are stationary; therefore, the proposed dynamic panel data model is feasible.

The main results of this study indicate that companies need time to adjust their capital structures to changing economic conditions. The dynamic panel models generated based on the panel data methods used show that the companies in this study use a partial adjustment mechanism to determine their capital structure. Thus, the level of leverage observed in a current period depends on that used in the previous period (persistence). In addition, the effect of lagged leverage is more pronounced in the short term than in the long term.

Traditional explanatory factors, such as size, profitability, tangibility, growth and debt-free tax shield, influence both listed and unlisted firms. Other factors, such as liquidity and dividends, are either insignificant or not representative. In general, the effects of these variables on capital structure conform to the Pecking order theory, except for the size variable whose effect aligns with the Trade-off theory, both for listed and unlisted companies. Regarding the control variables, the industry sector influences the capital structure of the two groups, while age is not significant for listed companies and is significant for unlisted companies.

The findings of this study indicate a prevalent reliance on equity capital over long-term leverage among Ecuadorian companies, potentially hindering growth opportunities based on external long-term financing. These highlight the importance of understanding the aspects of capital structure in Ecuador, particularly the differences between listed and non-listed firms, offering valuable insights for investors, financiers, and government officials.

It is essential to acknowledge two limitations in this study: firstly, the incomplete period of information for certain companies in the sample, coupled with challenges accessing additional data on potential determinants of capital structure. Secondly, there are unique contextual differences across various industry sectors. Addressing these limitations would facilitate a more nuanced understanding of the issues discussed, mitigating generalizations concerning financing access conditions and firms' capital structure approaches.

In summary, enhancing synergy between the productive and financial sectors is imperative in Ecuador's business landscape. Redirecting the focus from short-term financing to strategic capital structure initiatives could foster accelerated development within the country's business sector.

Efficiency of private banking

Banking efficiency is an issue of vital importance since, by its very nature, banking plays a predominant role in the development of the national economic and financial system. Therefore, the sustainability of banks will depend on the efficiency with which their operating resources are managed to generate production and profitability. However, bank management is subject to regulations that condition various aspects, such as lending and deposit interest rates and a set of financial indicators that must be maintained at predetermined ranges or levels. Within this regulatory framework, bank management must implement strategies that allow it to achieve its financial objectives, where each bank maintains efficiency levels that lead to sustainability and avoid the risk of bankruptcy.

Concerning the second objective of this thesis, the study of Ecuadorian private commercial banks is developed based on information from the annual financial statements of 18 private commercial banks from 2007-2017. In this context, we study efficiency from different non-parametric methodological approaches, described below.

Stochastic Frontier Analysis (SFA)

This method estimates efficiency considering multiple inputs and outputs, several explanatory factors of inefficiency, unobserved technological heterogeneity, and time-

varying efficiency. For this purpose, a stochastic frontier model with an output-oriented distance function in a Bayesian framework is used, and the cost-effectiveness approach is considered. Heterogeneity in production or costs is an important characteristic of firms, influencing their efficiency. Strategic management theories, such as the resource-based view of the firm (RBV) (e.g., Barney, 1991; Conner, 1991; Peteraf, 1993; Wernerfelt, 1984), emphasize the role of heterogeneous resources among firms in achieving competitive advantage. This heterogeneity can be caused by factors such as size, ownership, technology, firm characteristics, and managerial capabilities, among other factors described in the literature.

The general specification of our output-oriented production distance function is based on the translog-type stochastic production frontier model, in which we model unobserved technological heterogeneity and time-varying technical inefficiency, considering that the conditional mean of inefficiency depends on other banking and economic factors (covariates). Subsequently, we estimate our panel data model using a random parameter model in a Bayesian approach.

In the model, we use operating expenses, personnel costs, and interest expenses as inputs and consider the total amount of loans, deposits, and income (interest + fees) as outputs. In addition, we consider non-performing loans (NPL) as an undesirable output following recent banking research. We also include financial capital as a covariate in the frontier specification and linear and quadratic time trends to represent technological progress. As environmental factors explaining time-varying inefficiency, we consider some determinants: number of years in business, size, operating profitability, domestic or foreign ownership, and level of bank reserves.

Overall, the results show evidence of unobserved heterogeneity across banks and time-varying inefficiencies. In addition, time-varying efficiency scores are high and stable, and one factor that significantly explains inefficiency, but negatively, is foreign ownership, but not domestic factors such as operating profitability and reserve requirements imposed by the Central Bank of Ecuador. Finally, the estimated returns to scale show a bimodality that

indicates the existence of two groups of banks associated with decreasing and constant returns to scale.

This approach holds significant potential to provide valuable insights for bank managers regarding the short-term implications within the industry. Bank managers play a key role in operational efficiency, requiring diverse skills such as customer relationship, brand management, revenue, and budget monitoring. The results indicate that transient efficiency varies over time, forcing Ecuadorian bank managers to adapt to changes year by year. Ecuadorian bank managers should improve their management practices compared to their foreign counterparts. Although larger banks tend to increase market concentration, their financial results were lower than those of medium-sized banks after the study. That underscores the importance of analyzing operating expenses and revenue targets by product or service type. However, our results do not show that some environmental factors, such as bank reserve requirements, age, and operating profitability, influence efficiency.

This study recognizes some limitations. For example, the sample size of banks is relatively low despite an adequate number of periods. Therefore, future studies could cover other Ecuadorian financial institutions, including savings and credit cooperatives, to provide a more comprehensive analysis, considering new regulations to improve banking competitiveness. Additionally, other econometric approaches using the random parameter model could be introduced in the Bayesian framework, assuming other distributions for the inefficiency terms, such as the truncated-normal, which allows modeling the conditional mean over time as a function of covariates. In addition, future research could develop models that separate bank efficiency between transitory (non-systematic) and persistent (systematic) parts to avoid possible biased estimation of the overall inefficiency, especially if persistent inefficiency and unobserved heterogeneity (both or not) are present (Colombi et al., 2014).

Data envelopment analysis (DEA)

This study is framed in the context of increased regulation applied to banking in Ecuador after the crisis at the end of the last century that led to the dollarization of the economy. Particularly, in the period 2007-2017, some rules were accentuated, such as the regulation of

lending and deposit interest rates, reserve requirements, the maintenance of 10% of the loan portfolio, as well as the maintenance of adequate levels of provisions for uncollectible accounts (*loan loss provisions*, LLP), among other control measures. Consequently, this study highlights how certain regulatory factors affect banking efficiency, while the objective of these rules is to promote the sustainability of the banking system.

With DEA methodology, we analyze the efficiency of the same set of banks using multiple inputs and outputs. DEA uses radial and non-radial measures to evaluate the efficiency of DMUs (Ashrafi et al., 2013). Classical radial DEA models such as CCR (Charnes et al., 1978) or BCC (Banker et al., 1984) assume that there is a proportional change in inputs or outputs but do not account for slack in efficiency scores and can exhibit significant deviations (Deng et al., 2020). On the other hand, non-radial DEA measures, such as SBM (*slacks-based measure*), consider the slack in each input and output and allow for variations in both inputs and outputs, which are not proportional. SBM allows the separation of good outputs and undesirable or bad outputs, using variable returns to scale (VRS) technology) (Tone, 2003).

We used a methodology focused on a two-step procedure to estimate efficiencies. In the first stage, we apply a slack-based measurement (SBM) model that deals with undesirable outcomes, assuming VRS, which we contrast with a DEA-BCC model and the respective Bootstrap of both SBM and DEA-BCC models. In the second stage, we evaluate the effect of some economic factors used in previous studies on bank efficiency.

In the first stage, the inputs used in the efficiency models are operating expenses and personnel expenses, while the outputs are gross margin, total deposits, and total loan portfolio. In particular, we evaluate the effects of loan loss provisions (LLP) and non-performing loans (NPL) on banks' inefficiency by using them as undesirable output factors and measuring them separately.

In the second stage, we evaluate the effects of some covariates on the efficiencies obtained with the SBM models containing the undesirable outputs LLP and NPL. To do so, we estimate the effects from a censored Tobit regression using maximum likelihood. The

determinants or covariates used are linear trend time, years in business or age, gross profit portfolio, commercial business share, return on assets (ROA), market share, depreciation tax shield (NDTS), central bank required deposit rate (regulation), liquidity risk ratio (liquidity risk). In addition, we include a couple of categorical variables: stock market (listed banks) and ownership.

The main results show several facets. First, larger banks are more efficient than medium and small ones. Second, using non-performing loans as undesirable output represents higher slack-based inefficiency (SBM). And, third, using LLP overestimates banks' efficiency when used as undesirable output. Regarding the significant determinants in one or both models evaluated, bank age and the depreciation tax shield negatively influence efficiency, while market share and the deposit rate do so positively.

Overall, the results suggest Ecuadorian banking regulations' positive influence on efficiency. However, the NPLs reserve requirement seems counterproductive, negatively affecting efficiency by increasing capital ratios. An interesting fact is the positive trend in ROA, which could be due to the same regulation.

The study yields three key insights. Firstly, Ecuadorian regulations appear to promote financial deepening through interest rate control and mitigate non-performing loans (NPLs) via capital reserves. Secondly, these regulations demonstrably allow banks to adapt and maintain high efficiency. Finally, less efficient institutions can leverage the performance indicators of their counterparts for improvement.

The study acknowledges limitations. Expanding the sample to encompass diverse financial institutions beyond commercial banks within the analyzed period offers valuable scope for future research. Additionally, incorporating alternative explanatory variables, such as credit risk and liquidity, could enhance understanding of efficiency determinants.

Efficiency in the hotel industry

Analyzing efficiency in the Ecuadorian hotel industry is crucial for improving its competitiveness and long-term sustainability. Understanding efficiency levels makes it

possible to identify areas for improvement in operational processes and resource management, optimize the use of available resources, reduce costs, and increase the profitability of hotels, thereby improving the quality of services and customer satisfaction. In the context of high global competition, productive efficiency becomes a determining factor for the success of the Ecuadorian hotel industry. However, the entry into force of labor and accounting standards may condition competitiveness and efficiency in a sector such as the hotel industry, which is financially characterized by high levels of investment and fixed costs.

To answer the third objective of this thesis, we analyze the efficiency based on the formulation of an unbalanced data panel. This aspect results from companies' difficulties sustaining themselves in a highly competitive market over time. The data used to measure efficiency were taken from the annual financial statements published by the Superintendence of Companies, Securities, and Insurance of Ecuador from 2007 to 2017. With them, we formed a sample of 93 lodging companies operating in four regions of Ecuador: Costa, Sierra, Amazonia, and Galapagos.

This study uses a two-stage procedure to evaluate the determinants of the operating efficiency of the lodging industry in Ecuador. In the first stage, we estimated efficiencies based on a non-parametric mathematical programming approach for estimating frontiers with radial (DEA) and non-radial (SBM) methods. These mathematical tools allow us to evaluate the efficiency of a set of companies' efficiency, considering their different characteristics and resources. In addition, we have used the Bootstrap approach (bootstrap-DEA and bootstrap-SBM) to more accurately estimate the unknown distribution of efficiency scores, following the methodological sequence of Wang et al. (2020) from the procedure of Simar and Wilson (1998). For this, and based on the available data, we select the following inputs: the number of workers, labor expenses (wage cost plus employee benefits), material expenses (includes equipment expenses), and other expenses, while as output, we use total income.

In the second stage, we analyze the effect of several determinants (covariates) on the hotel efficiencies in Ecuador obtained in the different models of the first stage. For this, we apply linear regression models using Simar and Wilson's (2007) procedure based on truncated

regression for radial DEA methods, while for non-radial SBM methods, we use Tobit's censored regression. In both cases, we used maximum likelihood, and in the case of the Simar and Wilson procedure, we used 2000 bootstrap simulations for each efficiency score.

The determinants represent different aspects: regulatory characteristics, hotel company characteristics (economic and financial), and control variables. Regarding regulatory characteristics, we consider the adoption in 2010 of the International Financial Reporting Standards (IFRS) and the labor reform (Labor reform) that regulates the type of hiring as of 2008. Among the economic-financial variables, we consider the following: operating return representing management's ability to profit based on available assets; market share indicating the percentage of revenues obtained from the total market; level of indebtedness indicating the level of assets financed with debt; and age as a proxy variable for brand experience and reputation. Other categorical variables used are: size (to identify companies located in the top quartile concerning the value of their assets); whether the hotels are listed, to differentiate those traded on the stock exchange from those not listed on the stock market; whether the hotel is foreign-owned (to differentiate companies with foreign capital); the category that represents the quality status of each hotel; the legal structure to classify companies by type of partnership; and, finally, the region and province that indicate the regional and provincial location of each hotel.

The main results show that the Ecuadorian lodging industry operates with an overall efficiency above 70%, with a tendency to decrease over time during the period analyzed. When contrasting the models, the inefficient hotels detected with the DEA model became more inefficient with the SBM model; therefore, the efficiencies measured with the non-radial model were systematically lower than those of the radial model. From another point of view, the overall efficiencies in the Amazonia and Galapagos regions exceed those obtained in the Costa region, which in turn shows better results compared to the Sierra region. Finally, studying the inefficiencies generated by the inputs, higher overall scores are observed in the number of employees and personnel cost. When analyzing the behavior over time, it is noticeable that in 2007, at the price of the labor reform, the inefficiencies in the inputs were considerably lower than those obtained in later years, such as in 2011.

Concerning the determinants of efficiency in Ecuadorian hotels, we found that the effects corresponding to the statistically significant variables tend to be consistent in the set of models presented. The factors that positively and significantly influence efficiency are: labor reform, period of crisis, operating profitability, market share, size, and hotels listed on the stock exchange. In the opposite direction, the factors that have a negative and significant influence are: the adoption of international financial reporting standards and age.

The results lead us to conclude that Ecuadorian hotel managers can gain valuable insights from this study to increase their efficiency. Financial considerations include aligning performance objectives with financial reality, optimizing cost-to-revenue ratios, and managing debt leverage strategically. Regarding human resources decisions, these involve choosing sustainable hiring models and specializing by market segment. In terms of competition, they could share knowledge and form clusters to improve competitiveness. Regarding certain categories, older hotels assume higher maintenance costs and must consider modernization. Also, hotel managers can evaluate the advantages of going public, for example, benefiting from more accessible access to funds and increasing the company's prestige.

Finally, while there are limitations in data quality and sample composition, future research using surveys and incorporating additional factors can further improve the understanding of hotel efficiency in Ecuador. By implementing these recommendations and addressing the limitations, hotels can improve their efficiency and remain competitive.

Keywords: Capital structure, Trade-off theory, Pecking-order theory, Unit root tests, Dynamic panel data, banks, output distance function, translog stochastic frontier model, true random effects, efficiency, SBM, undesirable output, lodging firms, efficiency, DEA, slacks-based measure (SBM), bootstrap-DEA, bootstrap-SBM.

Table of Contents

Index of tables

Index of Figures

Chapter 1. Introduction

1.1. Motivation and objectives

Socioeconomic development uses as one of its fundamental pillars the flow of capital (financial resources), which, oriented to productive investment, has as an intrinsic determinant the long-term sustainability of companies, and this aspect is strongly related to the ability of companies to raise funds and ensure their return by maximizing investment. From worldwide scientific research, it has been found that companies in general, and SMEs specifically, can survive in economic environments that favor their development, and the case of Ecuador has its own particularities. Therefore, this doctoral thesis is motivated by the interest of identifying some factors that determine business financial performance, within a temporal space with an economic dynamism affected by different reforms to the legal norms imposed by the same government. For this purpose, this paper focuses on the structure of corporate financing in general, based on a regulated context of money markets such as private banks. On the other hand, it analyzes the performance of a sector with specific characteristics, such as the hotel industry.

By virtue of the above, the main objective of the doctoral thesis is to carry out an econometric analysis of corporate financial management in Ecuador. To achieve this objective, three specific objectives are listed and justified below.

1. Analyze the capital structure and its determinants in Ecuadorian productive enterprises. The purpose of this study is to identify factors derived from corporate financial management that affect financing decisions. The detailed analysis of each factor and its effect on the capital structure deepens the understanding of business operations in Ecuador.

2. Analyze the efficiency of private banks. This study contributes to determine the performance of banks under a period of increased government regulation. The importance of this analysis is fundamental to understand the aptitude of private banks to fulfill their role as financial intermediaries in the demand for financing from the productive sectors and society in general.
3. Evaluate the efficiency of the hotel industry. Ecuador is one of the countries considered a potential tourist destination due to its rich biodiversity. Consequently, it is interesting to study the impact of some government regulations on hotel efficiency.

1.2. Economic environment in Ecuador

Ecuador is one of the small emerging countries in Latin America facing the challenges of globalization and political turbulence in the region. After the global financial crisis of the last decade of the last century, which generated profound changes in Latin American economies, particularly in the banking system, the Ecuadorian government decided to dollarize the economy in 1999 to moderate inflation and reduce capital flight, as the main factors of economic and social imbalances. However, the economic and price imbalances of the monetary transition forced the government to promote strong control measures in the financial system.

In the context of the crisis, economic and social pressures pushed the country into a highly unstable government that had seven presidents between 1996 and 2007. Peculiarly, none of them led the government for a full constitutional term. However, in 2007, social pressure and the country's specific circumstances led to the presidency of Rafael Correa Delgado, who remained in power until 2017, culminating an interim period and two full constitutional terms. It is this period of governmental stability (2007-2017), marked by strong reforms to the laws, the central axis of this thesis.

In 2007, faced with an unstable economy and a country with deteriorated infrastructure, recurrent power outages and a political system in crisis, the new policy sought to address these challenges and revitalize the economy. Orbe León and Caria, (2019) refer to some of the main strategic policies promoted by the government to achieve this: Redefining the role

of the State, focused on ensuring that the market and the State serve the interests of society, rather than the interests of economic or political elites; Economic Sovereignty, aimed to reduce dependency on external factors and institutions by implementing measures to boost domestic production, consumption, and investment; Infrastructure, significant investments were made in infrastructure, particularly in the energy sector, to ensure long-term electricity supply, reduce reliance on fuel imports, and mitigate environmental pollution; Renewable Energy, such as solar and biomass, was a key aspect of the policy to enhance energy efficiency and reduce environmental impact. The policy also focused on initiating the construction of new hydroelectric power plants to meet future energy demand, thus ensuring sustainable energy generation. These policies were the basis for promoting a transition in the production matrix.

Díaz Rodriguez et al. (2019) point out that the change in the government's productive matrix was aimed at reducing the economy's vulnerability to external shocks, due to the dependence on oil exports and traditional sectors such as agriculture and mining. Another argument put forth was the need to move up the value chain by promoting industrialization and adding value to raw materials. This approach was seen as essential for increasing competitiveness, generating higher-value exports, and creating more jobs with better wages. Emphasizing the importance of technological innovation, the government highlighted the need to transition towards a knowledge-based economy (see Bonilla et al. (2021)) for an extensive description of this policy). This involved investing in research and development, fostering innovation hubs, and promoting the adoption of technology across various sectors to enhance productivity and competitiveness.

In the context of changing the productive matrix, the government policies also emphasizing the significance of sustainable development and environmental conservation. This included promoting renewable energy sources, implementing environmental regulations, and integrating sustainability considerations into economic policies to mitigate the negative impact of industrial activities on the environment. Lastly, the government framed the transition in the productive matrix to promote social inclusion and reduce poverty. By diversifying economic activities and creating more employment opportunities in non-traditional sectors, such as agribusiness, tourism, biotechnology, renewable energies and the

knowledge economy, among others especially in rural and marginalized areas, the aim was to improve living standards and reduce income inequality.

The Ecuadorian economy experienced several significant changes during the 2007-2017 period. Real GDP growth that exceeded the average achieved in the 1983-2006 period was observed, as well as an increase in public and private investment (Central Bank of Ecuador). Throughout this decade, the Ecuadorian economy showed higher per capita growth than in previous periods, and economic policies oriented towards "good living" were implemented. These changes occurred in a context of political stability and economic expansion, based on policies to reactivate investment, production, and consumption.

1.2.1. Business sector

During the 2007-2017 period, the productive business sector experienced the governmental paradigm shift. For example, access to resources and training programs so that companies could incorporate advanced technologies in their productive processes, which allowed them to improve their efficiency, quality, and competitiveness in domestic and international markets. With this, incentives to encourage productive diversification in support of companies seeking to invest in non-traditional sectors, promoting innovation and technology adoption. This included tax exemptions, preferential credits, subsidies and financing programs for projects oriented toward industrialization, technological innovation and sustainable development.

As part of the productive diversification strategy, the government sought to promote the internationalization of Ecuadorian companies and their access to new markets. Trade agreements were established, providing support for exports, and initiatives were promoted to improve the international competitiveness of companies, allowing them to diversify their sources of income and reduce their dependence on domestic markets. At the same time, regulations and policies were implemented to promote sustainable business practices, including stricter environmental standards, measures to protect workers' labor and social rights, and corporate social responsibility programs.

However, in the ranking of the World Bank (2020) report that analyzes the conditions for starting a business, out of 190 countries, Ecuador is in 177th place, while Peru and Colombia are in 133rd and 95th place. When filtering the ranking by region to consider exclusively Latin-American, Ecuador ranks 29th out of 32 countries, contrasting with Peru and Colombia's 19th and 11th positions, respectively. This means that, in terms of facilities for starting a business, Ecuador faces significant challenges compared to other countries. It is important to consider that this indicator evaluates various factors, such as the simplicity or difficulty of the procedures, the time required to register a company, the associated costs, and the efficiency of the process. According to the Latin American Bureaucracy Index 2017, small businesses in Ecuador had to spend an average of 395 hours per year to comply with bureaucratic procedures. This is equivalent to 49 working days or approximately 2.5 months of work for an employee who does not produce directly for the company but is mainly engaged in paperwork. On the other hand, when a company decides to close, it must comply with a series of procedures to liquidate its operations. If these formalities are excessive or confusing, the closing process can become costly and lengthy.

Around the corporate business sector, which is the subject of study in this doctoral thesis, the number of companies that submitted financial reports to the government control agency, went from 54,805 in 2008 to 72,765 in 2017, representing an increase of 32.8%. From another approach, in the same range of years, the investment in company assets grew 99%, because it went from 59.79 to 119.05 in billions of dollars. However, the level of external financing of company investments decreased from 66% to 43%. One aspect that could explain this fact is that most companies are small or medium-sized, and their bank loan products tend to be short to medium-term, usually requiring collateral. Among other reasons, this restrictive attitude by lenders is justified by the limited information quality provided by resource demanders (i.e., the situation is one of information asymmetry). Alternatively, companies might seek external financing from the stock market. Still, in Ecuador, policies to promote this option remain largely undeveloped, and most investors prefer to deal with large firms, with little regard for small and medium-sized companies.

1.2.2. Private banking

The Ecuadorian financial system is composed of three sectors: the public financial sector (including banks and other non-bank but state-regulated financial entities), the private financial sector (e.g., banks, mutual funds, finance companies and other financial entities) and the popular and solidarity financial sector (credit unions) (Monetary and Financial Policy and Regulation Board, 2016).

These sectors offer intermediation services, although with their own individual characteristics. For example, the public banking sector is mainly financed with state resources, and loans are earmarked for strategic national projects, for the development of municipalities, and to promote rural areas. These banking entities generally work with lower interest rates compared to private banks, as their target market is more specific and usually does not form part of the market segments of the other banking sectors.

Regarding the popular and solidarity sector, credit unions (savings and credit cooperatives) operate under a legal structure whose main characteristic is the solidarity of the members with their cooperative (Organic Law of Popular and Solidarity Economy, 2011). In other words, deposits come from cooperative members and credit risks are joint and several amongst entities. Until 2011, credit unions considered large (because of their portfolio and savings volume) were supervised by the Superintendency of Banks without losing their cooperative status. Subsequently, with the creation of the Organic Law of Popular and Solidarity Economy, savings and credit cooperatives came under the supervision and control of the Popular and Solidarity Economy Superintendency. The change was a government strategy to promote this financial sector as an alternative, and to expand financial inclusion to population segments not served by private banks.

Commercial banks carry out intermediation activities in the private financial sector. Approximately 75% of the banks meet multipurpose banking criteria, and 25% of them are

considered specialized banks.[1] Specialized banking mainly focuses on financing micro and small business segments with microcredits. In contrast, multipurpose banking mostly makes up their loan portfolio with consumer and commercial loans and, to a lesser extent, microcredit and mortgage loans. Multipurpose banking includes the largest banks (e.g., Pichincha, Pacífico, Guayaquil and Produbanco).

From another perspective, domestic private banking is predominant, as only one foreign bank (CitiBank) operates in Ecuador in the period under study (see Superintendency of Banks, 2022). This situation may be due to requirements imposed by the Monetary and Financial Policy and Regulation Board and the restrictions outlined in the Monetary and Financial Organic Code. For example, among others, the creditors of foreign bank cannot exercise rights over the assets in the Ecuadorian branch (ASOBANCA, 2019).

It is noteworthy that the situation of the Ecuadorian private banking system represented a formidable challenge in the 1990s under a banking deregulation policy (Patiño, 2001). As for Ecuadorian private commercial banks, from large old banks to others founded before 1990, 14 survived and ten failed (41.6%), while of the ten banks established in the 1990s, 50% failed and were dissolved and acquired by others. Therefore, the number of banks was reduced from 34 to 19 in 2000 (see Oleas-Montalvo, 2020).

In 1999, a series of domestic political and economic events, and the international financial crisis, damaged Ecuador's monetary policy instruments. Despite the measures adopted through legal reforms, the result was considerable capital flight and a sharp devaluation of the Sucre against the US dollar. Faced with the strong economic devastation and the lack of instruments to control the crisis, the government decreed severe restrictions on economic agents to avoid the banking system's collapse (Castillo Gallo, 2016; Jácome, 2004). Such a decision sought to slow down the effects of the crisis reflected in an economic recession, unemployment, migration, high inflation, and currency devaluation (Unda and Margret,

[1] According to the Monetary and Financial Policy and Regulation Board (2016), multiple banks are those with two or more credit portfolio segments with 20% or more of the total portfolio in each segment; and specialized banks are those with a credit segment representing more than 50% of the total portfolio and other segments not exceeding 20%.

2015). Consequently, in the 2000-2007 period, the controlling agencies of the Ecuadorian financial system implemented regulatory measures to reduce the probability of bankruptcy (Vera-Gilces et al., 2020). Yet, six other commercial banks failed between 2001 and 2014, two of which were inaugurated after dollarization.

1.2.3. Hotel industry

Ecuador is one of the world's megadiverse countries (ranked 6th) in the most compact territory. This feature is an advantage for tourism since tourists can move from one region to another over relatively short distances. The multiculturalism of different regional ethnic groups allows us to understand the ancestral knowledge of Ecuadorian people. This country also has rich architectural wealth represented mainly by the churches of the colonial era.

In line with its policies, the government of the day recognized tourism as a strategic sector within the new productive matrix, promoting actions to foster tourism development in the country. National and international promotion campaigns to attract tourists, the improvement of tourist infrastructure and the simplification of procedures for investment in the hotel sector were part of the strategies to attract tourists.

The growth in hotel supply was supported in part by temporary incentive programs and financial support for the development of the sector. This included preferential credits, tax exemptions and subsidies for the construction, renovation or modernization of hotels, as well as for the training of personnel in quality and service standards. The government also invested in the development of tourist destinations throughout the country, including urban and rural areas. This contributed to diversifying the tourism offer and distributing the economic benefits of tourism throughout Ecuador's territory.

'Four worlds in the same country' is Ecuador's tourism presentation pitch. The Andes Mountains cross the Ecuadorian territory forming a double mountain range with branches on the sides that naturally mark three continental regions: Costa (e.g., Guayaquil city with its important port, and the Spondylus tourist route (Moreno et al., 2022) (an opportunity to combine business and tourism recreation), Sierra (the cities of Quito and Cuenca have been

declared World Heritage Sites by UNESCO), and Amazonia (distinctive attractions such as the exotic gastronomy and ancestral healing based on native herbs, and scientific tourism due to the area's biological diversity (Izurieta et al., 2021)). The fourth region of the country is the Galapagos archipelago, formed by islands that emerged from the Pacific Ocean by submarine volcanic eruptions and declared by UNESCO as a Natural World Heritage Site in 1978 and a Biosphere Reserve in 1984.

According to data from the Ministry of Tourism, numbers of international tourists increased from 0.9 million in 2007 to 1.6 million in 2017. Together with domestic tourism, total tourism expenditure in 2007 was US$2025 million, and in 2016 reached US$4607 million. The increase in international inbound tourism also increased the capacity of the lodging sector to adapt to opportunities according to the characteristics of each location. Also, it is worth noting that the orography of the Ecuadorian territory motivates domestic tourism due to the travel times between regions, favoring the offer of lodging of different types and categories.

1.3. Structure of the thesis

The doctoral thesis is composed of six chapters and addresses three specific sectors in Ecuador. The first chapter corresponds to the introduction to the doctoral thesis. Chapter two corresponds to the business productive sector in general, chapters three and four deal with the private banking sector, and chapter five deal with the hotel sector specifically. Finally, chapter six presents the overall conclusions of the thesis, highlighting the relevant findings as well as the specific limitations of each study and suggestions for future research. The document ends with a bibliography and the appendix.

The follow is an introductory summary of the central chapters of the doctoral thesis.

1.3.1. Capital structure and its determinants

The second chapter, entitled "Target Leverage and Determinants of Firms' capital structure in Ecuador", focuses on corporate financial management by analyzing the

determinants of financing decisions. We hope to strengthen the content of this study in order to be able to publish it in a scientific journal.

In this context, we use a general dynamic panel data model based on an autoregressive of order p with strictly exogenous and endogenous variables as regressors, addressing two main aspects as contributions to this field. First, we incorporate target leverage and a partial adjustment mechanism, considering transaction or adjustment costs often overlooked in previous studies (Antoniou et al., 2016; de Miguel and Pindado, 2001). Second, we investigate the relevance of capital structure theories in Ecuador, an emerging market economy characterized by directed and dollarized features. Our empirical analysis focuses on key determinants such as profitability, size, growth, tangibility, liquidity, dividends, and non-debt tax shield, thereby contributing novel insights into financial management within the Latin American context. Concerning this chapter, we expect to generate a scientific article and send it to a specialized journal.

1.3.2. Efficiency of private banks

The third chapter resulted in a published article entitled *Heterogeneity and time-varying efficiency in the Ecuadorian banking sector. An output distance stochastic frontier approach*, (J. Salvador Cortés-García, J.V. Pérez-Rodríguez): *Quarterly Review of Economics and Finance* 93 (2024) pp. 164-175. The journal is ranked Q1 in the ASJC of SCOPUS, Q2 in JIF and Q1 in JCI of the JCR, and Q2 in SJR.

The article focuses on the efficiency of Ecuador's private banks by exploring heterogeneity in production or cost. This topic deals with heterogeneity as the fundamental element to understanding the intricacies of firm efficiency, particularly within the context of strategic management theories such as the firm's resource-based view (RBV).

This chapter contributes to the international literature on bank efficiency in two significant ways. Firstly, we evaluate the impact of utilizing the output distance function to model technological heterogeneity and time-varying inefficiencies within a panel data stochastic frontier analysis (SFA) framework. Our method employs a Bayesian context and

distinguishes itself from existing literature by modeling conditional mean inefficiency based on exogenous factors in a single-step procedure. Secondly, we examine the repercussions of banking sector restructuring and regulatory reforms on the efficiency of banks in Ecuador—a nation undergoing innovative changes in its productive model. This exploration is particularly relevant, considering the governmental reforms post-crisis, offering insights into the efficiency dynamics of an emerging economy during a transformative period.

The fourth chapter, entitled "*Assessing the effects of loan loss provisions and non-performing loans in bank's inefficiency",* complements the study of the Ecuadorian private banking sector. An article generated from this chapter is being reviewed in the *Spanish Journal of Finance and Accounting*.

This article focuses on the effect of government regulation on bank efficiency, among other factors. The international banking sector has experienced significant transformations driven by deregulation, globalization, financial innovation, and technological advancements (Girardone et al. (2007). These forces have systematically reduced the costs associated with information processing and transmission. The repercussions of these changes have been particularly impactful on the performance of banks worldwide.

This chapter contributes to the existing research by analyzing the effects of capital and accounting requirements using LLPs as a bad output and comparing their impact with non-performing loans (NPLs). The study aims to shed light on the simultaneous expansion of desirable outputs and contraction of NPLs using non-parametric and parametric models. The empirical research focuses on the Ecuadorian banking industry, providing insights into the efficiency of banks within the context of political stability and financial system reforms. The timely investigation considers Ecuador's experiences with banking crises, currency transitions, and subsequent stability, offering valuable lessons for other emerging economies facing similar challenges.

1.3.3. Efficiency of the hotel industry

The fifth chapter, "*Assessing the performance of the Ecuadorian hotel industry under a*

regulatory period", can be submitted to a scientific journal. This study shows the transformational evolution experienced by the Ecuadorian hotel sector since implementing government policies in 2007, primarily orchestrated through the Strategic Plan for the Development of Sustainable Tourism in Ecuador (PLANDETUR 2020).

Our study employs non-radial approaches, utilizing data envelopment analysis (DEA) and slacks-based measure (SBM) methods. The choice of non-radial methods is motivated by their ability to assess inefficiencies in inputs and outputs, accommodating simultaneous expansion and contraction—an aspect often overlooked by traditional radial models. Additionally, we employ a bootstrap approach to estimate the unknown distribution of efficiency scores, ensuring robustness and statistical reliability in our findings. This research contributes to the academic discourse on hotel efficiency assessment in emerging economies, offering insights valuable for both hotel managers and policymakers.

1.4. Data

The dataset used in this thesis comes from the financial reports of banks and companies, published by governmental control entities, such as the Superintendency of Banks and Superintendency of Companies, Securities and Insurance. To collect and organize the data, we obtained annual financial statements from 2007 to 2017 for each individual company or bank.

For chapter two, we constructed an unbalanced panel with annualized data for 292 listed and 10572 unlisted companies from 18 productive sectors. Regarding chapters three and four, we have an unbalanced panel includes 18 private banks classified into seven large banks, four medium-sized banks and seven small banks. The size classification was made based on 2017 financial information. Finally, for chapter five we formed an unbalanced panel with the financial information of 93 hotels geographically located in four regions.

Chapter 2. Target leverage and determinants of firms' capital structure in Ecuador

2.1. Introduction

For many years, most empirical studies undertaken to identify the determinants of firms' capital structure under theoretical approaches such as Irrelevance, Trade-Off, Pecking-Order, Agency Costs or Signalling, focused on listed companies, either in the USA (Bradley et al., 1984; K. Chung, 1993; Frank and Goyal, 2003; Titman and Wessels, 1988) or in Europe (Chittenden et al., 1996; Panno, 2003; Rajan and Zingales, 1995).

However, in the last two decades, this research focus has been significantly extended to consider the entire business sector, including both listed and non-listed firms, and also addressing emerging economies (Booth et al., 2001; Espinosa et al., 2012; Lemma and Negash, 2014). In the latter case, researchers have mainly considered the Trade-off and Pecking-order theories due to their greater explanatory power (Adair and Adaskou, 2015; Agyei et al., 2020; Czerwonka and Jaworski, 2021; de Jong et al., 2008; Huang and Song, 2006; Jiménez et al., 2013; Martinez et al., 2019; Silva Serrasqueiro et al., 2011; Stradomski and Schmidt, 2020).

The results obtained from these analyses vary significantly among the countries considered for several reasons. Firstly, studies of companies in related competitive environments (such as the G-7 countries) usually identify similar variables correlated with the capital structure, which is consistent with the theories employed (Rajan and Zingales, 1995). Secondly, differences in firms' structural and administrative characteristics generate important variations in the research findings obtained (Wald, 1999) regarding, for example, legal certainty (depending on the type of enterprise), the business risk associated with competition, and the country risk (which is relevant to interest rates). Third, each country's

institutional and economic factors influence business decisions and the capital structure generated (Booth et al., 2001; Wald, 1999).

The diversity of previous research findings shows that the Trade-off and Pecking-order theories complement each other (Kumar et al., 2017). Some financial determinants, such as profitability, liquidity and growth, behave by the Pecking-order theory; others, such as tax shield, size and tangibility, are in closer alignment with the Trade-off (or Static Equilibrium) theory. These considerations corroborate Myers' (1984) conclusion that an overarching capital structure theory must be devised and consolidated before giving managers meaningful advice.

The main econometric methods applied in previous investigations of capital structure determinants have used pooled regressions and panel data models based on fixed and random effects in a panel data framework and ordinary least squares with pooled data. However, the existence of transaction costs could bias the results thus obtained due to the presence of a dynamic relationship arising from lagged leverage, a consideration that researchers have traditionally neglected (Antoniou et al., 2016; de Miguel and Pindado, 2001; M'ng et al., 2017)

The present chapter makes two main contributions to the literature on the determinants of capital structure in emerging countries.

First, we consider the presence of target leverage and a partial adjustment mechanism consistent with transaction or adjustment costs (Antoniou et al., 2016; de Miguel and Pindado, 2001). This approach has been adopted in various studies of emerging countries, such as those by M'ng et al. (2017) in Malaysia, Singapore and Thailand; (Chakraborty, 2010) in India; Yu & Aquino (2009) in the Philippines; and Tristão & Sonza (2019) in Brazil. However, to our knowledge, the latter is the only study in Latin America.

Second, we analyse the relevance of the above theories to an emerging (directed and dollarised) market economy, namely that of Ecuador. Although Gutiérrez et al. (2018) and Sarmiento (2017) have analysed some capital structure determinants in this country, we focus in particular on the relevance of the main capital structure theories in this context, taking into

account that Ecuador underwent significant economic restructuring, during a decade of governmental and administrative stability, from 2007 to 2017. During this period, the continuity of the public administration facilitated the construction of a comprehensive statistical database for the corporate sector.

Following the Trade-off and Pecking-order theories, we analyse the following determinants of capital structure: profitability, size, growth, tangibility, liquidity, dividends and non-debt tax shield (Kumar et al., 2017). We test the theories locally, considering whether the stated factors are relevant to companies' financing decisions in Ecuador. In our opinion, this novel approach makes a valuable contribution to understanding financial management within an emerging country in Latin America characterised by a dollarised economy.

This chapter continues organized as follows: Section 2.2 describes the business context in Ecuador. Section 2.3 briefly reviews the literature on capital structure, including the empirical evidence provided and the particular case of Latin America and Ecuador. Section 2.4 describes the study method employed, based on dynamic panel data models. Section 2.5 contains the empirical analysis, the data considered, the main transformations and the results obtained from the estimation of static and dynamic panel data models. In Section 2.6 we present the results obtained and finally, in Section 2.7, we discuss these results and summarise the main conclusions drawn.

2.2. Capital Structures in Ecuador

Adopting the type of capital structure is among the most crucial initial decisions a company must take (Donaldson, 1961; H. Li and Stathis, 2017). Many theories argue that while this decision is usually adopted under internal considerations, a company's room for manoeuvre may be narrow in specific economic contexts. The resulting capital structure may be subject to the company's capabilities and the conditions of the money markets from which funds must be obtained (Fonseka et al., 2013). Large companies have the greater negotiating power to manage their target capital structures, while for most small and medium-sized companies, restricted access to money and capital markets reduces their scope for

determining external financing decisions (Adair and Adaskou, 2015; Cassar and Holmes, 2003; Stiglitz and Weiss, 1981)

During 2007-2017, the Ecuadorian government encouraged bank deepening to expand their credit supply to businesses and consumers. This policy significantly expanded the banking system's volume of deposits and loans (Torres Cumbicus, 2020).[2] However, although companies enjoyed more significant opportunities to access credit, extraordinary conditions and limitations were imposed. Nevertheless, trade credit grew by 154% during the above decade (Asobanca, 2021).[3]

2.3. Literature review

2.3.1. The main capital structure theories

Trade-off theory

Capital structure is one of the most widely-explored areas of corporate finance research. Modigliani and Miller (1958) established the starting point by proposing that the mode of financing adopted is irrelevant in determining the total value of a company. It has been suggested that these authors intended to represent the advantages of corporate borrowing if this option reduced equity capital and improved the company's return on equity.

Nevertheless, this proposition generated controversy because it did not consider the effects of market imperfections that make the cost of capital subject to business risk. Among such factors that limit and condition company borrowing are taxes, the costs generated in

[2] The volume of the total loan portfolio increased from 20% in 2007 to 39% of GDP in 2019. This indicator includes private banks, financial companies, mutuals, cooperatives and BanEcuador (Torres Cumbicus, 2020).

[3] According to information generated by the Datalab Asobanca website, in 2007 the commercial banking portfolio stood at US$ 587.1 million, and in 2017 it reached US$ 1,491.2 million (Asociación de Bancos del Ecuador [Asobanca], 2021).

providing and recovering funds, agency costs and the possibility of non-repayment due to bankruptcy (Donaldson, 1961; Myers, 1977; Robichek and Myers, 1966).

Modigliani and Miller (1963) revised the theory of irrelevance and introduced the effect of taxation on capital structure and company value. In their model, companies deduct debt interest from their profits, thereby achieving tax savings. In contrast, the cost of equity financing through the payment of dividends is not deductible (Jensen and Meckling, 1976). Theoretically, therefore, companies would prefer to raise funds through debt rather than equity. In this respect, Miller (1977) argued that if companies increase shareholder returns by acquiring higher debt levels, the capital structure becomes relevant in determining the firm's value.

From another perspective, excessive financial leverage can lead to perceptions of a higher risk of default, provoking insolvency costs (Baxter, 1967; Stiglitz, 1969). If the debt-to-capital ratio exceeds the limit investors tolerate, higher interest rates will probably be incurred, and shareholders will demand higher returns. Therefore, corporate indebtedness generates pressures to achieve sufficient profits to meet the expectations of all investors (creditors and shareholders). This conclusion underlies the Trade-off theory formulated by Kraus and Litzenberger (1973).

Under this theory, operating profits should be sufficient to cover debt interest, taxes and the shareholder returns required. It is important to note that in the event of bankruptcy, lenders have priority over shareholders, which generates a conflict between the financial objectives of each group of investors, bringing agency theory into play (Jensen & Meckling, 1976). Both circumstances give rise to agency costs and the perception of possible bankruptcy costs, which are difficult to specify. These arguments strengthen the relevance of capital structure and the possibility of a break-even leverage ratio. Therefore, the behaviour of those involved in providing company finance influences the capital structure created (Ritter, 2003).

Ross (1977) introduced the model of financial signalling for capital structure. This model suggests that when there is sufficient information for all participants in corporate finance, the resulting capital structure will be in equilibrium. However, investors' inferences may diverge

(Leland and Pyle, 1977), denoting the existence of information asymmetries (Akerlof, 1978). This understanding promoted the search for an alternative theory of capital structure.

Pecking-order theory

In business environments, the elements of capital structure are frequently subject to change, and therefore it is not easy to sustain a given capital structure over the longer term (Fama, 1980). For example, if the business risk varies because of turbulence in the economy, this will affect profit forecasts, interest rates and the firm's optimum capital structure. Consequently, company behaviour often does not provide a stable capital structure.

In this context, investors' doubts regarding the quality and quantity of information a firm holds will affect debt negotiations and costs. The awareness of problems arising from asymmetric information gave rise to the Pecking-order theory, in which firms prefer internal financing to issue securities. If external funds were needed, the firm's order of preference would be risk-free debt first, then risky debt, and finally equity (Myers and Majluf, 1984). This context means that the capital structure is not generated by the tax advantages accruing from the debt but by the effect of agency costs. In this respect, Fama and French (2002) argued that new equity and debt issuance costs affect the order of financing preferences.

As a first option, internal financing involves restricting dividend payments and increasing the cash available to finance corporate projects (Tamule et al., 1993). If the costs of holding cash are less than those of issuing securities, the tenets of the Pecking-order will apply.

2.3.2. Determinants of capital structure

Given the above literature background, we now analyse the relationships between specific determinants and capital structure theories.

Profit

For lenders, a firm's level of profitability demonstrates its ability to pay the interest and capital repayments due on a loan. At the same time, for shareholders, this parameter reflects the generation of value in their investments. Therefore, return on assets is a direct and high-

impact indicator influencing the capital structure (Chen, 2004). Trade-off theory suggests that high profitability will tend to increase levels of debt (Dammon and Senbet, 1988), while under Pecking-order theory, the reverse is true (Shyam-Sunder and Myers, 1999).

Size

The importance of company size (measured by assets) is that larger firms can more readily diversify their investments. In doing so, they dilute the cost of financing transactions and minimise the likelihood of bankruptcy (Rajan and Zingales, 1995; Titman and Wessels, 1988). In contrast, smaller companies that require external financing to sustain operations (Yildirim et al., 2013) may face problems of credit rationing and higher external financing costs (Martinez et al., 2019). The Trade-off theory suggests a direct association between size and leverage, while the Pecking-order theory suggests an inverse relationship.

Growth

Companies that rely on external borrowing are likely to limit new debt issuance to cope with asset growth (D. E. Allen, 1993). On the contrary, companies that favour equity financing will only resort to external funding to supplement their capital needs (Baskin, 1989). Accordingly, growth is negatively related to leverage under the Trade-off theory, while this relation is positive under the Pecking-order theory (L. Lang et al., 1996; Titman and Wessels, 1988).

Tangibility

Companies' concerns about the costs and risks of debt may generate an indirect relationship between tangibility and leverage (Fama and French, 2002). In contrast to this view, Frank and Goyal (2003) concluded that changes in investments in tangible assets are directly associated with the firm's external borrowing. Therefore, a positive relationship is expected under the Trade-off theory and a negative one under the Pecking-order theory.

Liquidity

Suppliers and short-term lenders generally require companies to maintain a sufficient liquidity ratio. In this scenario, the Trade-off theory directly relates liquidity and leverage.

On the other hand, high levels of liquidity reduce financing costs (Kulkarni and Chirputkar, 2014); hence, the level of liquidity is inverse to the level of leverage, according to the Pecking-order theory.

Dividends

Companies may seek to free up cash on hand by paying dividends, thus avoiding commitments to generate returns on idle capital (Ross, 1977). In essence, if the dividend payout ratio increases, external financing commitments are reduced. This behaviour aligns with the Trade-off theory, which directly relates dividend payments to leverage. On the other hand, under the Pecking-order theory, companies will seek to maintain sufficient slack, which translates into lower requirements for external financing (Fama and French, 2002).

Tax shield of capital spending

Miller (1977) and Graham (1996) demonstrated that high levels of taxation spur companies to issue debt. However, a debt tax shield is only feasible when operating profits are sufficient to meet financial expenses. Moreover, the joint impacts of depreciation and amortisation generated by capital spending could reduce operating income to a level that would render the tax shield on interest irrelevant (López-Gracia and Sogorb-Mira, 2008; Titman and Wessles, 1988). According to this argument, capital spending could result in lower company debt levels.

Age

The age of a company is synonymous with maturity in the money and capital markets (Serrasqueiro and Macas, 2012). In general, the quality of information companies discloses improves with age, thus gradually reducing investor uncertainty and enhancing conditions for accessing external financing.

Industry sector / Industry effects

Lenders perceive different levels of risk in companies according to the industry sector in which they operate (Cassar and Holmes, 2003). Previous studies have used the industry sector as a control variable to determine whether this factor is significant (Huang and Song, 2002;

Chen and Chen, 2011). In this respect, Michaelas, Chittenden, and Poutziouris (1999) indicated that the industry sector influenced the time elapsed until debt maturity.

2.3.3. International empirical evidence on the determinants of capital structure

2.3.3.1. Studies around the world

Theoretical capital structure models can be applied in developed countries and emerging economies. Studies in related competitive environments have reported similar results for determinants correlated with capital structure (Rajan and Zingales, 1995). However, differences in companies' structural and managerial characteristics may generate heterogeneity (Wald, 1999). In addition, factors emanating from each country's economic models may influence the capital structure management decisions taken (Booth et al., 2001; de Jong et al., 2008; Wald, 1999). An exciting aspect of this question is that different econometric models may be used to estimate the effect of determinants on leverage. Those most employed are ordinary least squares (OLS), fixed effects, random effects and the generalised method of moments (GMM) (see Appendix, Table A1). Table 1 summarises some of the primary research undertaken regarding theories and determinants of capital structure.

Many studies of capital structure focus on listed companies. Risk ratings for these firms encourage financial discipline, reducing data heterogeneity. In contrast, studies using non-listed companies tend to include samples from the same industry sector. However, a few studies have used large samples based on firms operating in different sectors.

2.3.3.2. Studies conducted in Latin America

In the following, we briefly consider the corporate environment in Latin America and research activity in this area.

Espinosa et al. (2012) examined the question of capital structure in the developing economies of Latin America. Specifically, these authors compared the capital structures of 466 US companies with those of 133 in Latin America (23 in Argentina, 50 in Chile, 41 in Mexico and 19 in Peru), using a data panel for 1998-2007. In general, the GMM model produced mixed results. In the USA and Chile, tangibility and size were significant explanatory variables, positively influencing leverage, while growth opportunity and performance were inversely associated with this factor. Similar results were obtained for the firms located in Mexico, except for company size, which was not statistically significant. In Argentina, tangibility was significant and positive, while growth opportunities and performance were significant and negative. In Peru, tangibility was significant and positive, and growth opportunities were inversely associated with market values. The most common finding among these Latin American countries was an inverse association between leverage and growth opportunities.

Forte et al. (2013) conducted a long-term study based on unbalanced panel data from 19,272 Brazilian SMEs from 1994 to 2006 and applied the OLS and GMM models to estimate the effect of the determinants. The results revealed a strong inverse correlation between profitability and total leverage and a weaker one with long-term leverage. In addition, there was a positive relationship between asset growth and leverage measures, which was more robust with total leverage and less with long-term leverage. Some authors found other significant determinants, such as size (positively related to leverage measures) and age (inversely related). These authors also investigated dynamic behaviour by including lagged leverage as an explicative variable, concluding that this variable is the best predictor of subsequent leverage.

Paredes Gómez, Ángeles Castro and Flores Ortega (2016) analysed a sample of 14 listed mining firms from Mexico, Chile, Colombia, Peru and Brazil, applying a fixed-effects model to a data panel from 2004 to 2018, incorporating one and two lags as explanatory variables. Their results show that tangibility increases leverage and profitability reduces it, while growth and size have no significant effect. In addition, the lagged values of the debt ratio are more robust determinants of the dependent variable than other explanatory variables.

In Ecuador, several recent studies have been conducted on capital structure. Cueva et al. (2016) used panel data samples for 113 companies in the textile sector, from 2000 to 2012, applying multiple regression with random effects where the dependent variable is financial leverage.4 The results show that the following variables are significantly associated with leverage: return on equity (positively), liquidity, inflation and net return on assets (all three, negatively). No such association was observed for GDP.

Sarmiento (2017) analysed the determinants of capital structure, focusing on profitability, size, tangibility, growth and taxes, in a sample of 844 manufacturing firms. This study used panel data from 2012 to 2015, applying fixed and random effects estimation models, and concluded that the fixed effects models were more efficient than the random effects ones. A significant direct relationship with leverage was observed for profitability, size, tangibility and taxes, and a significant indirect one for size. These findings are in line with the Trade-off theory.

Finally, Gutiérrez et al. (2018) conducted a similar study of the same manufacturing sector but limited to a sample of 304 companies in Guayaquil. These authors applied fixed and random effects models with panel data from 2012-2016. According to their results, the random effects model was efficient and apart from growth opportunities, the main determinants considered were significant. The profitability, tangibility and liquidity determinants were inversely associated with capital structure, while the size and non-debt tax shield presented a positive relation, thus corroborating the Pecking-order theory.

[4] The authors clarify that this indicator is different from the capital structure, and is calculated as follows: (BAI / Equity) / (BAIT / Total Assets).

Table 1. Empirical evidence on the effects of capital structure determinants and their theoretical implication (sign)

Trade-off theory (Sign)		Pecking-order theory (Sign)	
Panel A: Listed firms			
Profit			
Li & Cui (2003), Dragotă et al. (2008), Espinoza et al. (2012), Oliveira et al. (2013),	(+)	Titman & Wessles (1988), Chittenden et al. (1996), Booth et al. (2001), Huang & Song (2002), Frank & Goyal (2003), Chen (2004), Li & Islam (2019), Panno (2003), Dragotă et al. (2008), Yu & Aquino (2009), Jarallah et al. (2019), Espinoza et al. (2012), Ramjee & Gwatidzo (2012), Haron et al. (2013), Silva et al. (2020),	(-)
Size			
Booth et al. (2001), Huang & Song (2002), Panno (2003), Aivazian et al. (2005), Dragotă et al. (2008), Ramjee & Gwatidzo (2012), Haron et al. (2013), Jarallah et al. (2019), Silva et al. (2020)	(+)	Titman and Wessels (1988), Booth et al. (2001), Chen (2004), Aivazian et al. (2005), Oliveira et al. (2013)	(-)
Growth			
M. Jensen (1986), Titman & Wessles (1988), Chen (2004), Ramjee & Gwatidzo (2012),	(-)	Alipour et al. (2015), Silva et al. (2020)	(+)
Tangibility			
Huang & Song (2002), Frank & Goyal (2003), Chen (2004), Espinoza et al. (2012), Ramjee & Gwatidzo (2012), Oliveira et al. (2013), Li & Islam (2019), Silva et al. (2020)	(+)	Chittenden et al. (1996), Dragotă et al. (2008)	(-)
Liquidity			
	(+)	Panno (2003), Chakrabarti & Chakrabarti (2019)	(-)
Tax-shield			
Haron (2014), M'ng et al. (2017), Rani et al. (2019)	(-)	Bradley et al. (1984), Huang & Song (2002), Ramjee & Gwatidzo (2012), Silva et al. (2020)	(+)
Dividends			
Panno (2003)	(+)	Panno (2003)	(-)
Age			
Chaklader & Padmapriya (2021)	(+)	Chakrabarti & Chakrabarti (2019)	(-)
Industry sector			
	(+)	Al-Najjar (2011)	(-)
Panel B: Non-listed firms			
Profit			

	(+)	Cassar & Holmes (2003), Serrasqueiro et al. (2012), Adair & Adaskou (2015), Öhman & Yazdanfar (2017), Gregova et al. (2021)	(-)
Size			
	(+)	Serrasqueiro et al. (2012),	(-)
Growth			
Cassar & Holmes (2003), Serrasqueiro et al. (2012), Öhman & Yazdanfar (2017), Gregova et al. (2021)	(-)		(+)
Tangibility			
Chung (1993), Öhman & Yazdanfar (2017), Gregova et al. (2021)	(+)	Cassar & Holmes (2003), Serrasqueiro et al. (2012), Gregova et al. (2021)	(-)
Liquidity			
	(+)	Bandyopadhyay & Barua (2016), Öhman & Yazdanfar (2017), Gregova et al. (2021)	(-)
Tax-shield			
Silva et al. (2020); Serrasqueiro et al. (2012),	(-)		(+)
Age			
Rivera Godoy (2007)	(+)	Serrasqueiro et al. (2012), Palacín-Sánchez, Ramírez-Herrera, & di Pietro (2013) Adair & Adaskou (2015), Öhman & Yazdanfar (2017)	(-)
Industry sector (independent of any theory)			
Öhman & Yazdanfar (2017)	(+/-)	Yazdanfar & Ödlund (2010),	(+/-)

2.4. Methods

2.4.1. Target leverage and partial adjustment mechanism

Following de Miguel and Pindado (2001) and Antoniou et al. (2016), we consider the existence of target leverage and adjustment costs.

The following equation defines the target leverage ratio (LEV_{it}^{*}):

$$LEV_{it}^{*} = \sum_{k=1}^{K} \beta_k x_{k,it} + u_{it} \quad [1]$$

where $x_{k,it}$ is the *k*-th explanatory variable (usually strictly exogenous) for the *i*-th firm (*i*=1,…, *N*) in period *t* (*t*=1,…, *T*); $\beta = (\beta_1, ..., \beta_k)'$ is a vector of *K* unknown parameters for explanatory variables; and u_{it} is an error term, normally distributed with zero mean and constant variance. We can write the partial adjustment mechanism as:

$$LEV_{it} - LEV_{it-1} = \lambda \left(LEV_{it}^{*} - LEV_{it-1} \right), 0 \le \lambda \le 1. \quad [2]$$

where LEV_{it} and LEV_{it-1} are the observed current and one-lagged leverages, respectively, and λ is the adjustment coefficient. This mechanism assumes that firms cannot adjust their leverage quickly because of transaction costs. For example, if $\lambda = 0$ there is no adjustment in leverage, and when $\lambda = 1$ the adjustment is transaction cost-free (i.e., actual leverage is equal to target or desired leverage).

Substituting equation [2] into [1], we have the model:

$$LEV_{it} = \alpha LEV_{it-1} + \sum_{k=1}^{K} \theta_k x_{k,it} + v_{it} \quad [3]$$

where $\alpha = 1 - \lambda$, $\theta_k = \lambda \beta_k \ (k = 1, ..., K)$ and $v_{it} = \lambda u_{it}$.

Equation [3] can be empirically tested in a dynamic panel data framework.

An α coefficient between 0 and 1 signifies that the estimates are stable and that the leverage ratio will converge to its targeted level over time (Antoniou et al., 2016).

2.4.2. Econometric model

A general dynamic panel data model based on an autoregressive of order p with strictly exogenous and endogenous variables as regressors can be written as:

$$y_{it} = \sum_{j=1}^{p} \alpha_j y_{it-j} + \beta' x_{it} + \varepsilon_{it},\ i = 1,...,N, t = 1,...,T_i \qquad [4]$$

where y_{it} is the leverage for the *i*-th firm in the period *t*, and α_j is a measure of the extent of leverage persistence.

Following equation [3], equation [4] can be specified assuming *p*=1. In this case, when $|\alpha_1| < 1$, it is a stationary process.

Two estimators can be included in the dynamic panel data model proposed in equation [4]. Arellano and Bond (1991) developed the most frequently used estimator for dynamic panel data models. This estimator is constructed for datasets with numerous panels and few periods. However, its performance may be unsatisfactory if the autoregressive parameters are too large or if the variance ratio of the panel-level effect to that of the idiosyncratic error is too large. Accordingly, we also consider the Blundell and Bond (1998) system estimator, which uses additional moment conditions and obtains a more efficient estimation of the parameters than Arellano and Bond's (1991) (as shown by the large ratio of the variance of the panel-level effect to that of the idiosyncratic error). Both estimators are GMM-type.

2.5. Empirical analysis

2.5.1. Data

In Ecuador, the Superintendency of Companies, Securities and Insurance [SUPERCIAS] (2018) reported that 66053 companies were required to submit financial information in 2017. Our analysis is based on financial data from 10,572 non-listed and 292 listed companies. The sample includes companies that meet the following criteria: (a) continuous operation for at least five years; (b) book value of assets greater than 500,000 US dollars (to exclude micro-companies); (c) asset indebtedness larger than one or negative equity, to exclude companies controlled by creditors (Alcock and Steiner, 2017; Forte, Barros, and Nakamura, 2013; Cassar and Holmes, 2003). In addition, companies with very distant data were excluded. The financial data were adjusted to constant 2014 values.

Table 2. Firms and observations (n) by industry.

Code	Industry	Listed firms	Non-listed firms	Total
1	Agriculture and livestock	15	1255	1270
2	Mining	1	180	181
3	Manufacturing	79	1551	1630
4	Energy	0	48	48
5	Utilities	1	41	42
6	Construction	10	697	707
7	Trade	95	3461	3556
8	Transportation	9	501	510
9	Tourism	8	232	240
10	Communication	3	235	238
11	Insurance	33	148	181
12	Real estate	7	1033	1040
13	Professional services	14	542	556
14	Administrative services	11	352	363
15	Education	1	82	83
16	Health	2	135	137
17	Entertainment	0	31	31
18	Other	3	48	51
	TOTAL	292	10572	10864

Table 2 shows the sample composition by industry, according to Ecuador's International Standard Industrial Classification (ISIC).

Thus, an unbalanced panel was generated, with the data from 2007 to 2017. Four branches of activity predominate, accounting for 69% of the participation: commerce, manufacturing, agriculture and livestock, and real estate. The remaining 31% is distributed among the other fourteen classifications.

2.5.1.1. Variables

Leverage

Total leverage (LEV) and long-term leverage (LLEV) are the dependent variables most commonly used for measuring capital structure. Total leverage is important because it reflects the proportion of assets committed to external creditors. Long-term leverage, on the other hand, shows the company's willingness to make long-term investments. In this case, external investors often compare the long-term debt ratio to equity investment. We do not expect long-term debt to be more significant than equity in the present analysis.

Explanatory variables

As discussed in section 2.3.3.1, international capital structure studies frequently use explanatory variables such as return on assets, asset growth, tangibility, capital expenditure tax shield, dividends paid and liquidity. In addition to these, we incorporate the control variables age and industry sector (as have also been used in some empirical studies).

2.5.1.2. Descriptive statistics

In this study, we distinguish between listed and non-listed companies. Table 3 describes the coding and descriptive statistics for each variable considered.

The mean values obtained for the dependent variables LEV and LLEV for listed companies are 58% and 19%, respectively. For non-listed companies, the corresponding

values are 63% and 21%. We deduce that equity capital represents 42% of the capital structure for listed companies and 37% for non-listed ones. In other words, shareholders assume a higher proportion of risk than lenders in the composition of long-term financing.

Among the mean values of the explanatory variables, the average return on assets (PROF) is 11% for both samples. This indicator approximates the level of managerial performance that allows access to external financing.

The mean value for the size variable (SIZE) is higher in listed companies, while that for asset growth (AGROWTH) is higher in non-listed ones. We assume it is customary to include the largest companies in the sample of listed companies due to their greater capacity to trade securities. However, asset growth behaviour may respond to specific reasons in each case. For example, nominal changes in smaller companies may reflect more significant relative changes.

The mean value for the tangibility variable (TANG) is 41% in each sample. From this, we deduce that the average value for current assets is approximately 59%, meaning that most firms' investments are allocated to working capital.

The mean value for liquidity (LIQ) is 2.75 for the listed companies, which contrasts strongly with the value of 8.0 obtained for the non-listed companies. This significant difference reflects the type of working capital management employed by some companies; for example, if it were necessary to manage short-term liabilities at low levels, this would exacerbate the liquidity ratio.

The values for capital spending (i.e., non-debt) tax shield (NDTS) are 0.02 and 0.03 for listed and non-listed companies, respectively. This indicator is subject to application time and tax rules based on fixed assets. We suspect that this indicator decreases for each company over time and that larger companies invest in longer-term assets.

Table 3. Definitions of variables and descriptive statistics.

			Listed					Non-listed				
Code	**Name**	**Description**	**Obs.**	**Mean**	**Std**	**Min**	**Max**	**Obs.**	**Mean**	**Std**	**Min**	**Max**
Panel A: Endogenous variables												
LEV	Leverage	Total liabilities divided by total assets	2058	0.58	0.21	0.00	1.00	84554	0.63	0.26	0.00	1.00
LLEV	Long-term leverage	Total long-term liabilities divided by total assets	2058	0.19	0.14	0.00	0.89	84554	0.21	0.24	0.00	1.00
Panel B: Independent variables												
PROF	Return on assets	Earnings before income taxes, interest and depreciation, divided by total assets	2058	0.11	0.13	-1.18	0.96	84554	0.11	0.26	-6.97	31.55
SIZE	Size	Logarithm of total assets	2058	16.78	1.63	13.09	21.13	84554	14.69	1.19	13.08	21.24
AGROWTH	Asset growth	Total assets for period *n* minus total assets for period *n-1*, divided by total assets for period *n-1*.	1982	0.07	0.23	-0.75	2.09	74554	0.12	0.55	-1.00	30.35
TANG	Tangibility	Fixed assets divided by total assets	2058	0.41	0.25	0.00	1.00	84339	0.41	0.31	0.00	1.00
LIQ	Liquidity	Current assets divided by current liabilities	2058	2.75	20.04	0.05	875.13	84554	8.00	164.99	0.00	20709.16
NDTS	Tax shield of capital spending	Depreciation + amortisation, divided by total assets	2058	0.02	0.02	0.00	0.30	84554	0.03	0.04	0.00	1.16
DIV	Dividends	Dividends paid divided by net income.	2058	0.22	1.33	0.00	44.60	84554	0.32	6.95	0.00	1097.06
Panel C: Control variables												
AGE	Age	Years of life of each company	2058	33.16	17.34	6.60	96.80	84554	22.77	12.77	5.80	97.30
DIND	Industry sector	Branch of activity of each company according to ISIC	2058	7.19	3.86	1.00	18.00	84554	7.19	3.86	1.00	18.00

Notes: The DIV value is obtained as the difference between retained earnings accounts of two consecutive years; the Age variable moderates the effect of the independent variables; the Industry sector variable captures the differentiating effect by industry type. The number of observations for the AGROWTH variable is lower because the first year observed is the basis of the calculation for the following year's data; the LIQ variable shows a proportion of less than 1% of missing data. The Industry sector is described in Table 1.

The dividend variable (DIV) values are 0.22 for listed companies and 0.32 for non-listed ones, which suggests that companies generally finance their operations from profits.

The age variable (AGE) shows that the listed companies have an average age of 33.2 years, and the non-listed companies, 22.8 years, indicating that listed companies tend to have more experience than non-listed ones. Finally, for the industry sector variable (DIND), in both samples the most numerous sector is that of commerce (7).

Table 4 shows the correlations obtained among the independent and dependent variables. Most of the variables are significantly related at the 1% level. The variable DIV is insignificant for LEV, AGROWTH and NDTS in the listed companies and is only significant for LEV in the non-listed companies. The rest of the variables are directly or indirectly correlated, without showing any clearly-defined pattern of signs. Overall, the matrix shows low levels of correlation between the predictor indicators, which implies an absence of multicollinearity (Cassar and Holmes, 2003; Chen, 2004; Öhman and Yazdanfar, 2017).

Table 4. Pearson's correlations.

Panel A: Listed firms

	LEV	LLEV	PROFIT	SIZE	AGROWTH	TANG	NDTS	DIV	LIQ
LEV	1								
LLEV	0.464***	1							
PROFIT	-0.0613**	-0.102***	1						
SIZE	0.247***	0.136***	0.0103	1					
AGROWTH	0.136***	0.0565*	0.110***	0.0789***	1				
TANG	-0.218***	0.274***	-0.0673**	0.263***	-0.0578*	1			
NDTS	0.0520*	0.133***	0.241***	0.0892***	-0.0818***	0.301***	1		
DIV	0.000796	-0.0724**	-0.0652**	-0.0765***	0.0109	-0.0719**	-0.0341	1	
LIQ	-0.144***	-0.0524*	-0.0371	-0.0247	-0.0269	0.0310	-0.0441*	-0.00618	1

Panel B: Non-listed firms

	LEV	LLEV	PROFIT	SIZE	AGROWTH	TANG	NDTS	DIV	LIQ
LEV	1								
LLEV	0.410***	1							
PROFIT	-0.0641***	-0.0711***	1						
SIZE	-0.0296***	-0.0261***	-0.00753*	1					
AGROWTH	0.0677***	0.00911*	0.0158***	0.140***	1				
TANG	-0.274***	0.235***	-0.0619***	0.0193***	-0.0152***	1			
NDTS	-0.0668***	0.0519***	0.127***	-0.0767***	-0.0993***	0.287***	1		
DIV	0.00743*	-0.00691	-0.00202	-0.00390	-0.00321	-0.00687	-0.00291	1	
LIQ	-0.0595***	0.00420	-0.0110**	-0.0110**	-0.00701	0.0127***	-0.0103**	-0.00111	1

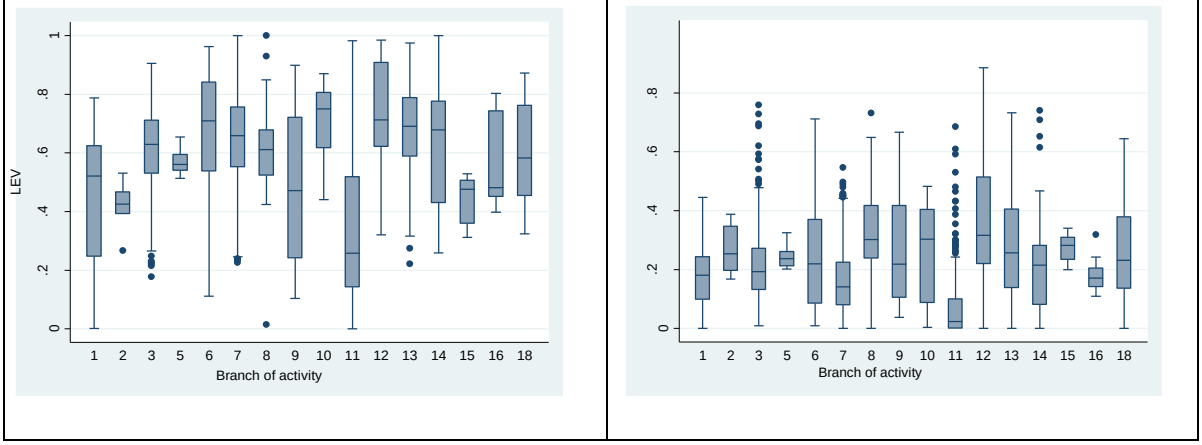
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 1 shows the behaviour of the dependent variables LEV and LLEV by industry, from another approach. Panel A shows that the median LEV by industry sector tends to be dispersed around the general average. On the other hand, the behaviour of LLEV in the three

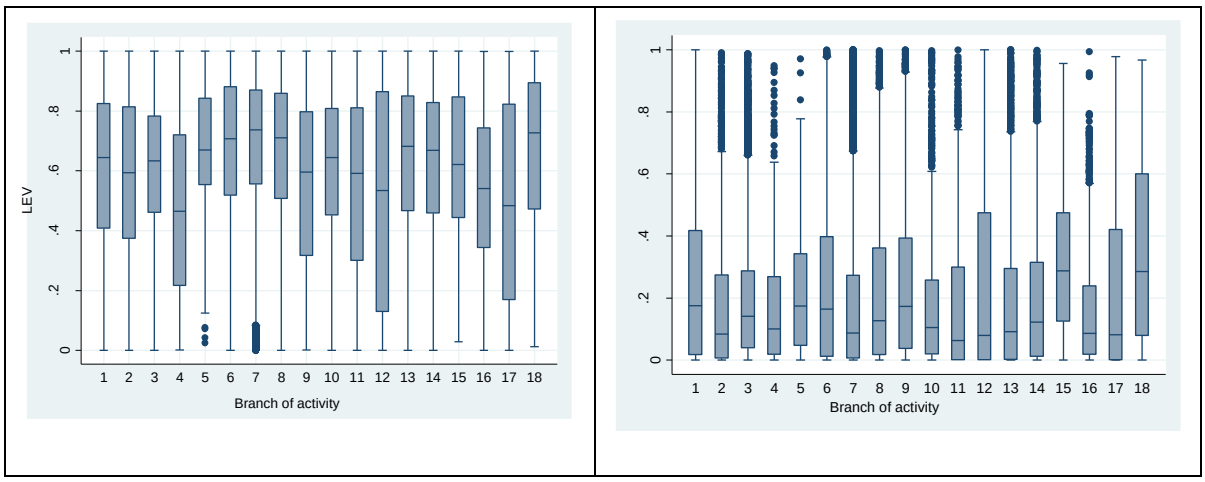
principal industries shows more dispersion in the values above the third quartile. In Panel B, the median LEV tends to cluster around the mean. In general, the value of the indicators is more dispersed between the minimum and the first quartile and more compact between the third quartile and the maximum. The opposite is true for LLEV, which shows that a significant number of companies have high levels of long-term leverage.

Figure 1. Empirical distribution for LEV and LLEV by industry.

Panel A: Listed firms.



Panel B: Non-listed firms.



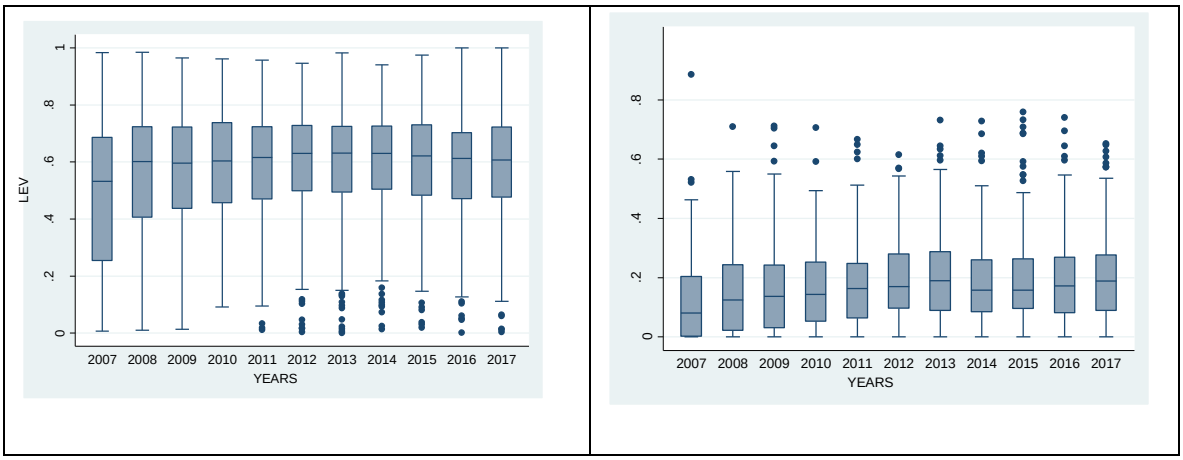
Notes: LEV and LLEV are measured in decimal expressions; Branch of activity (Industry sector) is described in Table 1.

Figure 2 shows that in the listed companies the median LEV remains stable over time. Notably, from 2010, the lower limit moves away from zero. The LLEV also evolves from 2010, becoming more disperse in the outer quartiles. Among the non-listed companies (Panel

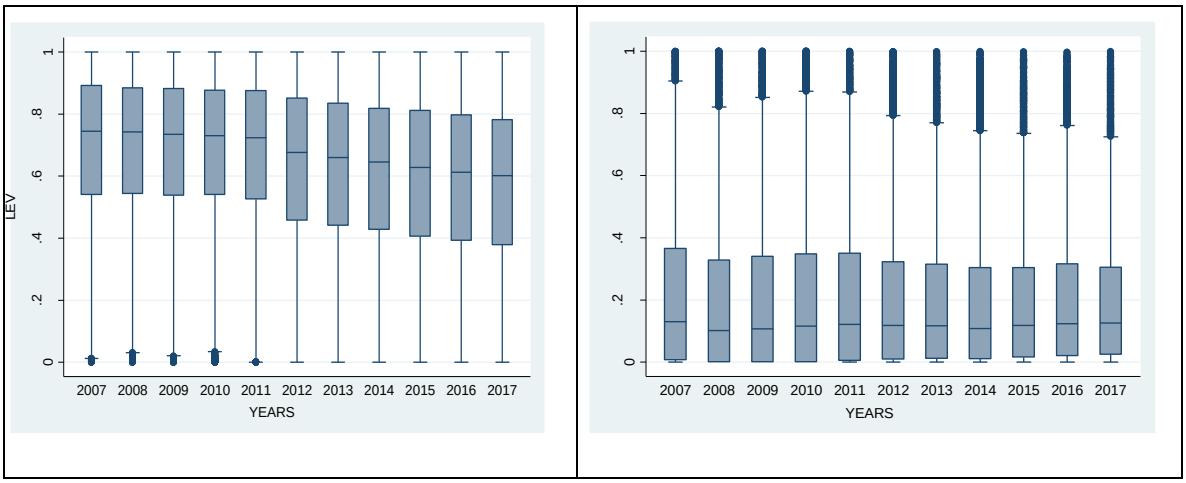
B), the median LEV and the interquartile range box both trend downwards, but expand from 2012. The LLEV, however, remains compact below the median, spreading towards the third quartile, and becoming more dispersed towards the maximum.

Figure 2. Time-path empirical distribution for LEV and LLEV.

Panel A: Listed firms.



Panel B: Non-listed firms.



2.5.1.3. Unit root tests

In this study, the analytical method varies according to the nature of the variables. In this section, we briefly explain the unit root tests performed and the dynamic panel data model obtained. In the panel unit root tests, independence among the firms is assumed. These tests are based on following ADF equation for panel data:

$$\Delta y_{it} = \rho_i y_{it-1} + \sum_{j=1}^{p} \delta_i \Delta y_{it-j} + x'_{it}\beta + \varepsilon_{it}, \quad [5]$$

where y_{it} is the series to be analysed and $i = 1,2,...,N$ are cross-section firms over periods $t = 1,2,...,T_i$. The x_{it} represents a column vector of exogenous variables, including any fixed effects or individual trends, ρ_i is the mean-reversion coefficient, p is the lag length of the autoregressive process, and ε_{it} is an idiosyncratic error assumed to be independent. It is noteworthy that when $\rho_i = 1$, then y_{it} presents a unit root. On the other side, if $|\rho_i| < 1$, then y_{it} is said to be weakly (trend-) stationary.

Focusing on ρ_i in the ADF model [5], we can use two types of tests. First, we can test for the null hypothesis of a unit root against the alternative of no unit root, using the Breitung (2001) and Levin et al. (2002) approaches and test for the null of no unit root against the alternative hypothesis of a unit root using the Hadri (2000) approach. We assume that the persistence parameters are shared across firms in both cases, so $\rho_i = \rho$ for all *i*. Second, we can test the null hypothesis of a unit root against the alternative hypothesis of specific individuals without unit roots. To do this, we allow ρ_i to vary freely across firms, enabling individual unit root processes. This is the case of the ADF and PP tests proposed by Maddala and Wu (1999) and Choi (2001) and the IPS test proposed by Im et al. (2003). The possible deterministic components employed are Fixed Effects, and Fixed Effects with individual trends.

Table 5 summarises the results of the Fisher-type panel unit root test for no cross-dependence (by using STATA), which works well with an unbalanced panel.

In general, these results suggest that the null hypothesis of all panels containing unit roots should be rejected, and therefore we conclude that some panels are stationary. As indicated by Pesaran (2012), it should be noted that a rejection of the null hypothesis of the panel unit root should be taken as evidence that a statistically significant percentage of the units are

stationary.[5] This result indicates that the proposed dynamic panel data model can be estimated.

Table 5. Panel unit-root test results.

	Non-listed firms				Listed firms			
Variables	**ADF – Fisher Chi-Square**		**PP – Fisher Chi-Square**		**ADF – Fisher Chi-Square**		**PP – Fisher Chi-Square**	
	Fixed	**Trend**	**Fixed**	**Trend**	**Fixed**	**Trend**	**Fixed**	**Trend**
LEV	4.30	4.19	5.83	7.06	817.54	1215.36	1285.14	1691.93
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
LLEV	5.26	4.63	7.29	8.18	945.51	507.60	1922.53	2054.29
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
PROFIT	4.80	4.22	6.84	8.26	1339.49	1270.00	1676.15	1834.42
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
SIZE	4.34	3.65	6.15	7.14	1288.64	851.44	1486.81	1511.09
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
AGROWTH	4.81	4.35	1.26	1.09	1091.47	1161.17	3545.33	2858.28
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
TANG	4.87	4.20	6.39	7.32	1037.52	854.41	1694.71	1981.85
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
LIQ	4.70	4.15	7.75	8.94	1525.76	1051.59	2115.11	1783.54
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
NDTS	4.57	4.04	6.33	7.57	1539.08	1119.86	1776.74	1448.87
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
DIV	4.22	3.91	5.01	5.19	1321.97	1090.44	1210.81	1082.86
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Number of firms	10572	10572	10572	10572	291	291	291	291

***Notes*:** The table only includes the Fisher-type panel unit root test, which assumes no cross-dependence between firms. Other tests cannot be used, due to computational problems. The individual unit root test null hypotheses (ADF and PP – Fisher chi square) are considered. Fixed and Trend represent the deterministic components of the tests: fixed indicates individual effects, and the trend indicates individual effects and individual linear trends. In all tests, a single lag is used. The p-values appear in brackets. Year dummies are not included. All statistics for non-listed companies are divided by 1×10^4.

[5] Alternative approaches to this question are discussed in Ng (2008) and Chortareas & Kapetanios (2009), among others.

2.5.2. Estimation results

Tables 6 and 7 show the LEV and LLEV results obtained for listed and non-listed companies, using OLS, fixed-effects, random-effects and dynamic panel data models. These tables include several dummy variables (firm, industry sector and year effects) as well as several hypothesis tests on the firm fixed effects, namely the Hausman test of random vs. fixed effects, the Arellano-Bond test for serial correlation in the first-differenced errors (AR(1) and AR(2), respectively), and the Sargan test of over-identifying restrictions (the null hypothesis is that all restrictions are valid). Finally, these tables show the R^2 of the OLS and fixed effects estimates, the total number of observations and the number of firms.

The test results shown in Tables 6 and 7 clearly show that the fixed effects are preferable to the pooled data (OLS) in terms of the F-test statistic (firm fixed effects). In addition, the fixed-effects model is preferable to the random effects one, according to the Hausman test result, since the null hypothesis of random effects is rejected. Moreover, many empirical studies in which panel data are used to analyse capital structure focus on fixed effects (see Appendix 1). Our results reflect a similar preference over random effects.

With respect to the dynamic model, the maximum autoregressive lag selected for the endogenous variable was one, because the coefficients were insignificant for higher orders. The moment conditions used by the system estimator in the leverage equation are valid because there is no serial correlation in the idiosyncratic errors at the 1% significance level. Nevertheless, these moment conditions are invalid in the long-term leverage equation, where the autocorrelation of first-differenced errors at order two is rejected. In neither case does the Sargan test of overidentifying restrictions lead us to reject the null hypothesis. This outcome corroborates the null hypothesis that the overidentifying restrictions are valid.

The dynamic model results presented in Tables 6 and 7 show that the coefficient of the one-lagged leverage variable is statistically significant and positive, indicating that there is a correlation between the levels of leverage in two consecutive periods. In other words, the null hypothesis of $\alpha_1 = 0$ equation [2] (i.e., no autocorrelation or no state dependence) is rejected. Moreover, this coefficient is less than one (absolute value), and therefore the panel

model can be globally stationary. This result supports the existence of a partial adjustment mechanism or a "persistent habit". Therefore, the fit between the desired (or optimal) and the actual leverage levels is significant.

This positive effect would be consistent with the findings of de Miguel and Pindado (2001), Frank and Goyal (2003), and M'ng et al. (2017), among others. It is also interesting to note that this coefficient is higher for the leverage equation in the short term than in the long term, which would indicate that the persistence or adjustment mechanism is lower in the long term than in the short term. This important finding indicates that long-term debt adjusts more slowly than short-term debt. Finally, in the dynamic model, the coefficients of the determinants that explain the capital structure also show interesting results, for both leverage (LEV) and long-term leverage (LLEV).

2.5.2.1. Short-run effects

According to the p-values in Tables 6 and 7, respectively, most of the coefficients of the independent variables tend towards significance, confirming the relevance of the variables included.

For listed companies, the PROFIT coefficients are significant and negative at 1% for LEV and 5% for LLEV, denoting that an increase of one unit in this variable reduces LEV by 0.133 and LLEV by 0.081; this pattern is in line with the Pecking-order theory. In the opposite direction, the SIZE coefficients are significant and positive at 1%; therefore, an increase of one unit in SIZE implies an increase of 0.064 in LEV and LLEV, in accordance with the Trade-off theory. Other determinants, such as AGROWTH (0.037) and TANG (-0.144) are significant for LEV while NDTS (0.577) is significant only for LLEV. All of these results are in line with the Pecking-order theory.

Concerning non-listed companies, the effects of PROFIT and SIZE are similar to those found for listed companies. The PROFIT coefficients are significant and negative at 1%, generating a reduction of 0.044 in LEV and 0.013 in LEV for each unit increase. For SIZE, the coefficients are positive, increasing by 0.076 in LEV and 0.013 in LLEV.

Table 6. Estimation results of panel data models for listed firms.

	Leverage				Long-term leverage			
	OLS	**Fixed effects**	**Random effects**	**Dynamic model**	**OLS**	**Fixed effects**	**Random effects**	**Dynamic model**
Variables								
One-lagged leverage				0.436***				0.358***
				(0.0417)				(0.0337)
PROFIT	-0.106***	-0.0398*	-0.0456**	-0.133***	-0.0840***	-0.0598**	-0.0658***	-0.0806**
	(0.0324)	(0.0215)	(0.0214)	(0.0242)	(0.0258)	(0.0249)	(0.0239)	(0.0329)
SIZE	0.0121***	0.0624***	0.0323***	0.0644***	-0.00239	0.0352***	0.00610	0.0641***
	(0.00322)	(0.00766)	(0.00533)	(0.00958)	(0.00256)	(0.00889)	(0.00446)	(0.0136)
AGROWTH	0.0721***	0.0280***	0.0373***	0.0307***	0.0451***	0.0142	0.0251**	0.0108
	(0.0165)	(0.00908)	(0.00902)	(0.00820)	(0.0131)	(0.0105)	(0.0102)	(0.0113)
TANG	-0.240***	-0.136***	-0.156***	-0.144***	0.112***	0.114***	0.120***	0.0512
	(0.0179)	(0.0196)	(0.0181)	(0.0229)	(0.0142)	(0.0228)	(0.0184)	(0.0317)
LIQ	-0.000728***	-0.000170*	-0.000241**	-0.000139	-0.000199	3.93e-05	-3.07e-05	8.09e-05
	(0.000177)	(9.86e-05)	(9.89e-05)	(9.82e-05)	(0.000141)	(0.000114)	(0.000112)	(0.000136)
NDTS	0.913***	-0.121	-0.0518	-0.274*	0.232	0.323*	0.234	0.577***
	(0.178)	(0.150)	(0.146)	(0.150)	(0.142)	(0.175)	(0.156)	(0.206)
DIV	0.00587**	0.00349**	0.00348**	-6.64e-05	-0.00357*	-0.00174	-0.00202	-0.00264
	(0.00266)	(0.00159)	(0.00160)	(0.00148)	(0.00212)	(0.00185)	(0.00181)	(0.00204)
Control variables:								
AGE	-0.00223***		-0.00276***	-0.00246	-0.000916***		-0.00127***	0.0107
	(0.000246)		(0.000545)	(0.00250)	(0.000196)		(0.000387)	(0.00893)
Firm Fixed Effects	NO	YES	NO	NO	NO	YES	NO	NO
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.440***	-0.423***	0.0966	-1.009***	0.166***	-0.491***	0.0250	-1.533***
	(0.0585)	(0.131)	(0.0938)	(0.196)	(0.0466)	(0.152)	(0.0772)	(0.376)
R-squared	0.419	0.141			0.253	0.045		
F-test (Firm Fixed Effects)		32.81 [0.00]				10.12 [0.00]		
Hausman test			75.80 [0.00]				40.48 [0.00]	
AR(1)				0.00				0.00
AR(2)				0.07				0.83
Sargan test				0.02				0.01
Number of firms	291	291	291	290	291	291	291	290
Total observations	1,982	1,982	1,982	1,955	1,982	1,982	1,982	1,955

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. AR(1), AR(2) and Sargan tests show p-values.

Table 7. Estimation results of panel data models for non-listed firms.

	Leverage				Long-term leverage			
Variables	**OLS**	**Fixed effects**	**Random effects**	**Dynamic model**	**OLS**	**Fixed effects**	**Random effects**	**Dynamic model**
One-lagged leverage				0.623***				0.4651***
				(0.00913)				(0.0076)
PROFIT	-0.0961***	-0.0363***	-0.0404***	-0.0441***	-0.0503***	-0.0162***	-0.0208***	-0.0128***
	(0.00336)	(0.00222)	(0.00220)	(0.00238)	(0.00316)	(0.00263)	(0.00256)	(0.0033)
SIZE	0.00575***	0.0384***	0.0259***	0.0763***	-0.00232***	0.0171***	0.00735***	0.0134***
	(0.000774)	(0.00153)	(0.00120)	(0.00222)	(0.000728)	(0.00181)	(0.00122)	(0.0029)
AGROWTH	0.0201***	0.0112***	0.0134***	0.0156***	0.00251	0.00244**	0.00384***	0.0035**
	(0.00163)	(0.000982)	(0.000967)	(0.00110)	(0.00153)	(0.00116)	(0.00113)	(0.0015)
TANG	-0.188***	-0.0793***	-0.102***	-0.115***	0.185***	0.135***	0.156***	0.1047***
	(0.00340)	(0.00403)	(0.00365)	(0.00512)	(0.00320)	(0.00477)	(0.00401)	(0.0071)
LIQ	-7.71e-05***	-2.28e-05***	-2.75e-05***	-1.04e-05***	4.88e-06	1.24e-05***	1.16e-05***	1.70e-05***
	(5.43e-06)	(3.29e-06)	(3.28e-06)	(3.41e-06)	(5.11e-06)	(3.90e-06)	(3.84e-06)	(4.62e-06)
NDTS	0.0490*	-0.00594	-0.0239	-0.0706***	-0.0935***	0.00374	-0.0255	-0.0040
	(0.0252)	(0.0223)	(0.0213)	(0.0260)	(0.0237)	(0.0264)	(0.0243)	(0.0360)
DIV	0.000257*	6.64e-05	7.40e-05	-6.20e-05	-0.000193	-0.000205**	-0.000216**	-0.0003***
	(0.000139)	(8.16e-05)	(8.14e-05)	(8.47e-05)	(0.000131)	(9.65e-05)	(9.56e-05)	(0.0001)
Control variables:								
AGE	-0.00473***		-0.00572***	0.0138***	-0.00158***		-0.00204***	-0.0352***
	(7.21e-05)		(0.000168)	(0.00346)	(6.78e-05)		(0.000147)	(0.0114)
Firm Fixed Effects	NO	YES	NO	NO	NO	YES	NO	NO
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.799***		0.482***	-0.962***	0.225***		0.106***	0.0604
	(0.0121)		(0.0182)	(0.113)	(0.0114)		(0.0184)	(0.178)
R-squared	0.169	0.113			0.0728	0.0135		
F-test (firm Fixed Effects)		20.65 [0.00]				9.62 [0.00]		
Hausman test			539.71 [0.00]				210.65 [0.00]	
AR(1)				0.00				0.00
AR(2)				0.02				0.00
Sargan test				0.02				0.01
Number of firms	10,528	10,528	10,528	10,483	10,528	10,528	10,528	10,483
Total observations	74,416	74,416	74,416	71,664	74,416	74,416	74,416	71,664

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. AR(1), AR(2) and Sargan tests show p-values.

Also, Tables 7 and 8 show that some determinants as AGROWTH, TANG and LIQ are significant and consistent with the Pecking-order theory for LEV. In contrast, TANG and NDTS corroborate the Trade-off theory for LLEV. Finally, the variable DIV is significantly and negatively related to LLEV; however, the coefficient is relatively small.

2.5.2.2. Long-run effects

The dynamic models generated reveal the short and long-run effects corresponding to each variable. Table 8 shows the long-run results for the models estimated in Tables 6 and 7, respectively.

Table 8. Long-run effects for listed and non-listed firms.

Variables	**Leverage (LEV)**	**Long-term leverage (LLEV)**
Panel A: **Listed firms**		
PROFIT	-0.24	-0.08
SIZE	0.11	0.06
AGROWTH	0.05	0.01
TANG	-0.26	0.05
LIQ	-0.00025	0.00008
NDTS	-0.49	0.58
DIV	-0.00012	-0.00264
Panel B: **Non-listed firms**		
PROFIT	-0.12	-0.02
SIZE	0.20	0.03
AGROWTH	0.04	0.01
TANG	-0.31	0.20
LIQ	-0.00003	0.00003
NDTS	-0.19	-0.01
DIV	-0.00016	-0.00056

To estimate the long-run effects, we must build the ratio: $\hat{\beta}_k / (1-\hat{\alpha}_1), k = 1,...,K$ indicative of the *k*-th explanatory variable. For example, in Panel B, the coefficient -0.12 for PROFIT is obtained by dividing -0.0441/(1-0.623). Clearly, this value is greater than the short-term effect (-0.0441) in absolute value, indicating that the long-term effect is higher than the short-term effect.

In general, these results show that the coefficients for the short-term effects (Tables 6 and 7) are lower than those for the long-term ones (Table 8).

2.6. Discussion

2.6.1. Listed firms

Regarding the short-term effects represented in the dynamic model (Table 6), most of the determinants are significant and in line with Pecking-order theory.

PROFIT is negatively related to leverage measures, as held by Pecking-order theory. The LEV coefficient is significantly related, reinforcing the hypothesis that listed companies prefer to use internal resources before resorting to external financing. These results are in line with the majority of previous research findings, both for developed economies (Antoniou et al., 2016; Serrasqueiro et al., 2012;) and for developing ones (Chakraborty, 2010; de Jong et al., 2008; Dragotă et al., 2008; Espinoza et al., 2012; Forte et al., 2013; Rodrigues, de Moura, Santos, and Sobreiro, 2017).

SIZE is significantly and positively related to LEV and LLEV, in accordance with the Trade-off theory (Booth et al., 2001; Titman and Wessels, 1988) and corroborating previous studies carried out elsewhere. For example, de Jong et al. (2008) considered 42 countries, only five of which (Belgium, Brazil, Mexico, Switzerland and Turkey presented a negative relationship between SIZE and LEV. In our study of the situation in Ecuador, the similarity in the coefficients is interesting given the composition of the total leverage. One of the main characteristics of the Ecuadorian securities market is the tendency of companies to issue short-term debt security (commercial paper) and long-term obligations with quarterly or semiannual amortisations, a behaviour comparable with bank financing.

AGROWTH is significantly and positively related to LEV, which is in accordance with the Pecking-order theory, and also coincides with previous research findings, such as the study of Iranian companies by Alipour et al. (2015) and the work of Silva et al. (2020) in Portugal. Although the impact is relatively low in our study, it is of interest because it again

provides evidence of the control exercised by financial managers in shaping the capital structure of listed companies.

TANG is inversely associated with LEV, following Pecking-order theory and as reported previously by Montalván (2019). This effect has also been observed in the USA (K. Chung, 1993), the United Kingdom (Walsh and Ryan, 1997) and France (Adair and Adaskou, 2015). In contrast, some studies have found empirical evidence of a positive relationship, including Chen (2004) in China, M'ng et al. (2017) in Malaysia, Singapore and Thailand and Silva Serrasqueiro and Rêgo Rogão (2009) in Portugal. Thus, it appears that listed companies in Ecuador prefer to finance their fixed asset investments from internal funds.

NDTS positively influences LLEV and presents a negative relation with LEV, as held by the Pecking-order theory. However, we cannot exclude the possibility of a positive relationship if the tax shield generated by fixed-assets depreciation is of sufficient importance (Antoniou et al., 2016).

In contrast to Panno (2003), we did not find that LIQ or DIV had any representative impact on capital structure.

2.6.2. Non-listed firms

Table 7 also presents the short-term effects of the dynamic model, but for non-listed firms. In this case, the negative relationship observed between PROFIT and the leverage measures is in line with the Pecking-order theory. Although the relationship is only moderate in LLEV, it strengthens in LEV. These results are similar to those found by Forte et al. (2013) for Brazilian companies and to those of Öhman and Yazdanfar (2017) in their study of Swiss companies. In our case, the PROFIT level might be insufficient to induce a negative sign in the relationship between variables, especially considering the local conditions regarding access to financing.

SIZE has a positive and significant influence on LEV and LLEV. The effect is weak in LLEV and moderate in LEV, a difference that is to be expected since long-term debt financing is a relatively minor part of total financing in Ecuador. As these companies are

non-listed, we assume that their financing is obtained from the money market (banking system) and/or spontaneous sources such as merchandise suppliers. This behaviour is similar to that found by Cassar and Holmes (2003) for Australian firms, and is aligned with Trade-off theory; it also coincides with the findings reported by Sarmiento (2017) and Gutiérrez et al. (2018).

AGROWTH presents a significant direct relationship with LEV and LLEV. Although the coefficients are lower than those found by Forte et al. (2013) and by Palacín-Sánchez et al. (2013) in Spain, they are similar in behaviour, since the coefficient for LEV is higher than that for LLEV. The difference between coefficients leads us to assume that Ecuadorian companies supplement their funding needs with short-term debt after using retained earnings, which is in line with the Pecking-order theory.

TANG shows a significant inverse relationship with LEV and a direct one with LLEV. This finding seems reasonable, because the ratio of LLEV to LEV is one-to-three. The specific debt terms adopted would help identify the theory that is most applicable (i.e., Trade-off or Pecking-order). Cassar & Holmes (2003), Öhman and Yazdanfar (2017), Sarmiento (2017) and Gutiérrez et al. (2018) all reported similar results.

Both LEV and LLEV bear significant relationships with LIQ (inverse and positive, respectively). The coefficients are weak, as were those found by Öhman and Yazdanfar (2017) for LEV. Similar results have also been reported by Rani et al. (2019) for companies in India and by Gregova et al. (2021) for firms in Slovakia, the Czech Republic, Poland and Hungary. We conclude, therefore, that companies with better liquidity indicators tend to use less external financing, thus evidencing the Pecking-order theory.

The NDTS variable was found to be significant and negative for LEV, but was not significant for LLEV. Given the impact of the NDTS coefficient on LEV, this result fits the Trade-off theory. Similarly, Öhman and Yazdanfar (2017) found a negative significance for LLEV, while Serrasqueiro et al. (2012) identified significant inverse relationships for the same variables in older Portuguese SMEs. On the contrary, there is empirical evidence in other studies in which NDTS is insignificant for LEV (Gregova et al., 2021; Rani et al., 2019;

Silva et al., 2020). We believe these discrepancies are related to tax rules and the business environment.

Although it has a relatively low impact, the DIV variable is statistically significant and negative only for LLEV. Other studies with large samples, by Öhman and Yazdanfar (2017) and Forte et al. (2013), do not use this variable.

Chapter 3. Heterogeneity and time-varying efficiency in the Ecuadorian banking sector. An output distance stochastic frontier approach

3.1. Introduction

Heterogeneity in production or cost is an important issue which should be accounted for in firm efficiency studies. It is worth noting that strategic management theories such as, the resource-based view (RBV) of the firm (e.g., Barney, 1991; Conner, 1991; Peteraf, 1993; Wernerfelt, 1984) highlights the role of heterogeneous resources among firms in achieving competitive advantage.[6] This heterogeneity is related to the resources companies possess, which are not perfectly mobile, causing heterogeneity to be maintained over time (Barney, 1991). This aspect could characterize unobserved technological differences between firms, which could arise from, for example, size and ownership. But other elements could also justify unobserved heterogeneity, for example, unexpected variations in firm characteristics or managers' ability to foster staff productivity.

In a technological heterogeneity context, it is reasonable to assume that production (cost or profit) technology could not be the same across firms because firms cannot share a common frontier. Particularly, it could distort estimated efficiency (production, cost or profit) if they were not considered in the panel data modeling (W. Greene, 2005; Tsionas, 2002). Notably, most bank efficiency papers using panel data models (e.g., (Pessarossi and Weill, 2015; Proença et al., 2023; among others) do not separate cross-bank heterogeneity from

[6] It is worth noting that there are other strategic management theories that can justify this issue such as the environmental model theory by Porter (1980). See Arbelo et al. (2021) for an excellent overview of this and RBV theories.

efficiency when they estimate efficiency in a panel data context. To our knowledge, few papers are disentangling the bank efficiency and heterogeneity in a panel data context. It is worth noting that those which did used non-standard panel data models based on random parameters models, which allow banks to be heterogeneous based on the idea that they don't have to share the same common cost (or production) function, i.e., the same vector of parameters in the cost (production) model (Tsionas, 2002). In general, these studies have used different approaches, such as cost functions to estimate bank cost (e.g., Barros and Williams, 2013; Goddard et al., 2014; Greene, 2005; among others), output distance functions (e.g., Feng and Zhang, 2014) or input distance functions (e.g., Galán et al., 2015) to estimate efficiency. For example, Barros and Williams (2013) in a two-step procedure proposed to model the cross-bank heterogeneity in the parameters of the bank cost function since they better accommodate heterogeneity and produce more precise estimated efficiencies, They explained bank estimated cost inefficiency in a second-step based on several factors (e.g., merger and acquisitions following legislative reforms, quality of assets adopting international accounting standards, capitalization, age, and diversification). Results have shown that cross-bank heterogeneity existed when bank efficiencies were estimated.

To our knowledge, no empirical banking studies have studied technological unobserved heterogeneity and time-varying inefficiency using an output distance stochastic frontier framework. This approach allowed us to model the conditional mean inefficiency over time by considering several economic and banking factors explaining inefficiency in a one-step approach.

Therefore, this chapter aims to contribute to the body of literature on bank efficiency at the international level in two ways. First, we evaluate the effect of using the output distance function to model technological heterogeneity and time-varying inefficiencies in a panel data SFA framework. We use an output distance function stochastic frontier model with random parameters because we consider multi-input and output technology and technological heterogeneity, such as Feng and Zhang (2014), in a Bayesian context. However, our paper differs from Feng and Zhang's (2014) because we model conditional mean inefficiency depending on exogenous factors to estimate time-varying efficiencies in a single-step procedure, which is statistically more efficient. We compare several time-varying efficiency

models in a Bayesian context, being a fixed parameter model and random parameter model distinguishing randomness of the constant term (similar to the true random effects model by Greene, (2005) and both the constant and input coefficients using a profitability approach. We also consider factors explaining the conditional mean inefficiency. And second, determining the impact of banking sector restructuring and regulatory reforms on the efficiency of banks in Ecuador. For example, Ecuadorian financial system control agencies implemented measures to reduce the probability of bankruptcy between 2000 and 2007. Then, the public administration promoted laws to restructure the financial system to ensure its solvency between 2007 and 2017. Thus, we analyze the banking market of an emerging country that experienced an innovative change in its productive model. In the case of Ecuador, we consider it relevant to study banking efficiency in a period characterized by the Government's administrative continuity and its reforms in the post-crisis period.

The empirical application is focused on a sample of Ecuadorian commercial banks from 2007 to 2017. These banks represent the majority of banks operating in Ecuador, both domestic and foreign-owned, which reached a volume of assets equivalent to 37.4% of the national GDP in 2017, in contrast to 26.9% in 2007. Also, the volume of the credit portfolio represented in 2017 was 23.6% while deposits were 29.4%. Finally, this sample comprises different commercial banks in terms of the size of assets in Ecuador during the analyzed period, including large, medium, and small banks.

The rest of this chapter is structured as follows: Section 3.2 briefly outlines the Ecuadorian banking industry. Section 3.3 describes the literature on heterogeneity and bank efficiency. Section 3.4 shows the stochastic frontier analysis to determine bank efficiency using the output distance function in a Bayesian context. Section 3.5 presents the data and empirical results, and finally, the main conclusions drawn are presented in Section 3.6.

3.2. Ecuador's banking industry

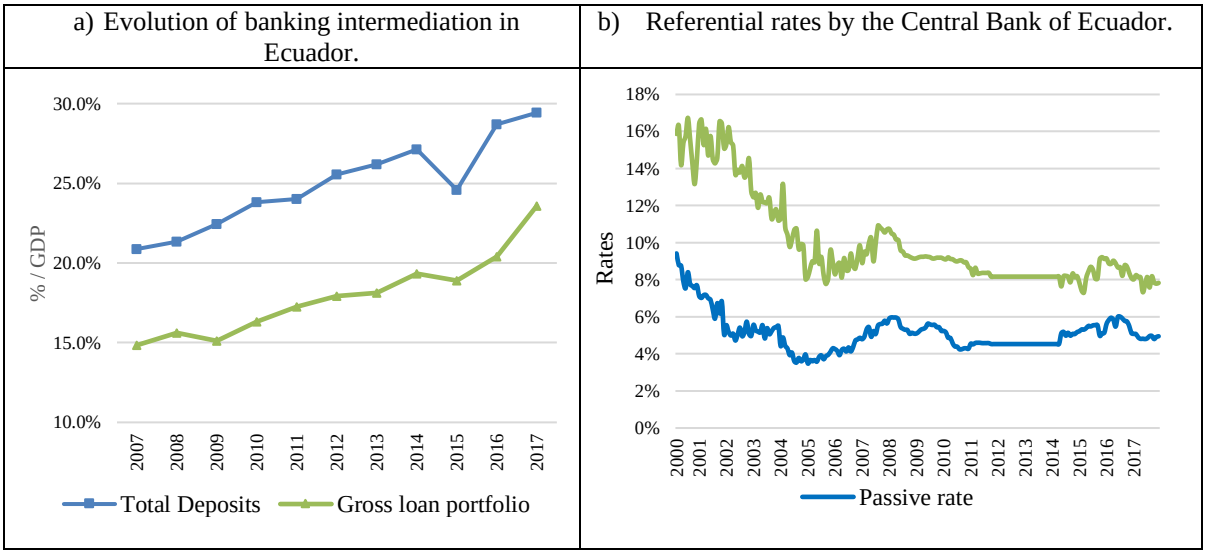
Ecuador joined the Latin American banking crisis between 1994 and 2000, following Argentina as one of the countries with the highest banking bankruptcy rate (45%) after Mexico (36%), Chile (22%), and Brazil (21%) (see Goddard et al., 2014). Public policies to deal with banking crises differ among Latin American countries. For example, in Mexico, foreign banks' mergers and acquisitions of domestic banks were facilitated as an exit strategy from the financial crisis of the late 1990s (Barros and Williams, 2013). Other Latin American countries that showed evidence of openness to foreign banking in that crisis period were Argentina, Brazil, Chile, Colombia, Costa Rica, Peru and El Salvador (see Ballescá, 2007; Yeyati and Micco, 2007). In these countries, liberalization of the entry of foreign investment was one of the public strategies to solve the banking crisis and improve banking competitiveness. In Ecuador, however, policies in this area were in the opposite direction.

History has shown that in some political-economic scenarios, the applicable regulation does not guarantee that the banking system can withstand financial shocks derived from the internal behavior of a particular country or the effects of trade globalization (Benston and Kaufman, 1996). Ecuador's economic, political, and social turbulence led to a change in government administration that lasted ten years (2007-2017). That administration promoted laws to restructure the financial system to ensure its solvency.[7] Weisbrot et al. (2013) refer to the obligation of banks to maintain a liquidity fund for emergencies and specific procedures in the event of insolvency of any bank. In addition, 10% of the deposits received must be deposited in the Central Bank. Rules were imposed to regulate interest rates, limit tariff rates on various financial transactions, raise taxes on bank income and improve controls on the entry and exit of foreign currency through the banks (Unda and Margret, 2015). Therefore, observing the leading banking productivity indicators (deposits, loans, and interest rates) is interesting when subjected to such conditions (Figure 3).

[7] Other relevant events were the adoption of Basel III standards, as well as the design of internal controls focused on preventing money laundering (Superintendency of Banks, 2010).

Figure 3 shows the bank depth and reference interest rates. Figure 3a depicts the annual evolution of deposits and loans as a percentage of GDP. The difference between them was narrow until 2008, indicating a higher liquidity risk during excessive withdrawal of deposits. Also, an increase in reserve funds to protect bank liquidity can be observed from 2009 onwards. Note that the difference between deposits and loans is wider from 2009 to 2014 due to bank liquidity protection measures. The notable contraction of these indicators in 2015 can be explained by some factors that affected the economy. For example, the fall in oil prices led to a decrease in public investment, the depreciation of the dollar and its effect on inflation and imports, and unpopular fiscal and tax policies such as the inheritance and capital gains taxes that generated uncertainty in the country.

Figure 3. Bank depth and reference interest rates.



Notes: Total deposits and gross loan portfolio represent the percentage share of GDP annually (data from ASOBANCA, 2023). The passive rate is the minimum base rate imposed by the Central Bank of Ecuador for fixed-term government deposits; the active rate is the maximum conventional rate for loans to state development projects (data from the Central Bank of Ecuador, 2023). Both passive and active rates are on an annual basis, adjusted monthly.

Figure 3b illustrates the effect of regulation on annual interest rates adjusted each month, comparing a specific annual loan interest rate (active rate) with a base annual deposit interest rate (passive rate). The 2000-2006 period exhibits a downward trend in rates, while the intermediation margin trend reduces from 2007. This behavior of the banking depth and net interest margin indicators, affected by government regulations, promotes interest in measuring the efficiency of this industry in the period under study.

The Central Bank of Ecuador regulates other loan interest rates classified according to credit segments or borrowers. Table 9 shows some Ecuadorian banking indicators. Particularly, Table 9 (Panel A) shows the evolution of the most representative loan interest rates. A comparison of interest rates between 2007 and 2011 shows a reduction in the gross spread. In general, loan interest rates have remained unchanged since 2009, while the interest rate for deposits fluctuated between 5.4% and 7.5% in 2007-2017.

In this scenario, even with the growth of intermediation indicators, the economic and financial performance of the banking sector declined (Table 9, Panel B). For example, the return on equity (ROE) varied from 19.78% in 2007 to 10.36% in 2017, while the return on assets (ROA) decreased from 1.76% to 1.03%. Small banks show instability and difficulties in financial performance, while large and medium-sized banks reduced their profitability significantly between 2007 and 2017. Although large banks reported lower ROE compared medium-sized banks in 2017, they increased their market power in the three leading indicators of bank concentration (Table 9, Panel C).

We can observe that bank concentration in assets, deposits, and loans experienced variations throughout 2007-2017. Deposits showed the highest concentration in 2017 (63.3%), followed by loans (62.9%) and assets (62.5%). Although the behavior of Ecuadorian banking concentration leads to an oligopolistic structure (see Romero-Galarza et al., 2020; Uzcátegui-Sánchez et al., 2018), the evolution of the indicators shows that regulations are slowing down their expansion. For example, the banking concentration shows slight increases in assets and deposits (between 2% and 3%), while in loans, the growth is higher (5.7%).

The Ecuadorian bank concentration levels are higher than those in other Latin American countries after the crisis and after the reforms applied between 1994 and 2000. Goddard et al. (2014) reported that the concentration ratio in Brazil and Mexico reached 55% and 56%, respectively, but this did not occur in Argentina and Chile, where the ratio remained close to 40%. However, these authors used the three-firm concentration ratio.

In conclusion, combining the dollarization of the economy and the banking system reforms seems to favor the financial system's sustainability. On the one hand, the financial

performance of medium-sized banks demonstrates management's ability to improve financial profitability. On the other hand, large banks require greater fundraising and placement of resources at the expense of profitability. However, the combination of the strategies of both groups hinders the development of new competitors and the sustainability of small banks.

Since state-owned banks respond to government policy interests and credit unions assume their own risks, our study focuses on private commercial banks.

Table 9. Some Ecuadorian banking indicators.

	2007	2011	2017
Panel A: Maximum APRs[(a)]			
The interest rate for deposits			
Deposits-360 days	5.6%	5.4%	7.1%
The interest rate for loans			
Productive corporate	12.3%	9.3%	9.3%
Corporate	12.3%	10.2%	10.2%
SMEs[(b)]	16.6%	11.8%	11.8%
Consumption	22.5%	16.3%	17.3%
Real State	14.0%	11.3%	11.3%
Microcredit	30.9%	25.5%	25.5%
Panel B: Financial performance			
ROE			
Large banks	24.26%	20.95%	9.78%
Medium banks	20.38%	17.71%	12.75%
Small banks	-2.53%	9.65%	1.74%
All banks	19.78%	18.91%	10.36%
ROA			
Large banks	2.12%	1.86%	0.93%
Medium banks	1.58%	1.39%	1.27%
Small banks	-0.37%	1.37%	0.30%
All banks	1.76%	1.68%	1.03%
Panel C: Banking concentration (four largest banks)			
Assets	60.2%	62.6%	62.5%
Deposits	60.1%	62.4%	63.3%
Loans	57.2%	60.9%	62.9%

Notes: Data from ASOBANCA (2023). [(a)] APR means the effective annual percentage rate. [(b)] SMEs stand for small and medium-sized enterprises.

3.3. Literature review

This section briefly discusses heterogeneity and efficiency, commenting on the approaches developed to tackle the problem. Then, it compares the empirical evidence provided in those papers which have employed the random parameter models and other model estimates obtained from traditional methods in a panel data context. In this sense, we distinguish between costs and output distance function findings. A final subsection focuses on efficiency studies of Ecuadorian and Latin American banks.

3.3.1. Heterogeneity and efficiency

It is worth noting that standard panel data models (e.g., fixed and random effects models) generally used to estimate efficiency in stochastic frontier analysis (SFA), confound any time-invariant cross-firm heterogeneity with the inefficiency term and do no treat them separately; therefore, they cannot correctly model efficiencies in the presence of heterogeneity (W. Greene, 2005). Greene (2005) showed that this aspect can seriously distort estimated inefficiencies. For example, the cross-firm heterogeneity in the parameters of the production (cost) function in a stochastic frontier analysis could distort the measure of inefficiency and provoke that parameter estimates be it was were not considered in a panel data stochastic frontier model (W. Greene, 2005; Tsionas, 2002). Therefore, inefficiency and unobserved heterogeneity must be modeled separately within the model to distinguish the two effects. This is the main issue of non-standard panel data models when considering heterogeneity in the modeling.

One way to model heterogeneity in a panel data context is to consider the possibility that the parameters of the production or cost functions are random. The main characteristic of this approach is that this model relaxes the restrictive assumption of a common production technology across firms (W. Greene, 2005; Tsionas, 2002). For example, Tsionas (2002) introduced a stochastic frontier model with random coefficients to separate technical inefficiency from technological differences across firms in a Bayesian framework.

Greene (2005) used a random coefficient model for banks that resembles the random parameter model proposed by Tsionas (2002) using a Bayesian estimator He proposed a special case of the random parameters model that produces a random effects model, preserving the central feature of the stochastic frontier model and accommodating heterogeneity, and examined random parameters and latent class models. In both cases, explicit models for firm heterogeneity are built into the stochastic frontier. As Greene (2005) commented, the advantage of the 'classical' approach developed in his paper is that it provides a means of building a model for the distribution of inefficiency and the production frontier. His modeling allows the isolation of firm heterogeneity while better preserving the mechanism in the stochastic frontier model that produces estimates of technical or cost inefficiency. For example, the true random effects model of Greene (2005) introduces randomness into the constant term (a specific effect) and separates it from the efficiency term.

Estimating the random parameter models is not simple and requires a high computational effort. For example, the parameters of the random parameter model by Greene (2005) can be estimated by the maximum simulated likelihood framework. See Tsionas (2002) and Greene (2005) for an excellent overview of the estimation procedure.

3.3.2. Empirical evidence of heterogeneity and bank efficiency

3.3.2.1. Heterogeneity in cost functions

Many papers have studied banks' time-varying cost efficiencies, including covariates (environmental factors) in the conditional mean, or variance equations corresponding to the inefficiency term to account for observed heterogeneity. Hence, several studies have incorporated variables inherent to the environment, organizational structure, size, or other factors (e.g., regulation, crisis periods, groups and regional characteristics, and financial variables) considered relevant to explaining inefficiency. For example, Lang and Welzel (1999) used an unbalanced panel of all Bavarian (Germany) cooperative banks for 1989-1997 to estimate a frontier cost function with a time-varying efficiency. They showed that a merger's positive scale and scope effects arise if the merged unit closes part of the former

branch network. Christopoulos et al. (2002) estimated the Greek banking system's cost efficiency (1993–1998) using a heteroscedastic (instead of homoscedastic) frontier model. Huang and Kao (2006) measured generalized production risk from a single output production function to a multiple output cost frontier, which can simultaneously examine input-oriented technical efficiencies and production risk in the context of panel data. Finally, Huang et al. (2017) proposed the copula-based simultaneous stochastic frontier model. Composed of a cost frontier and two output price frontiers for the banking sector, the stochastic meta-frontier model of Huang et al. (2014) was applied to estimate and compare cost efficiency and market power across five European countries from 1998 to 2010.

Focusing on technological heterogeneity in an SFA context, there are few applications of non-standard stochastic panel data frontier models where cost functions have been used to address random varying coefficients in a panel data context in the bank efficiency literature.[8] For example, Greene (2005) estimated a stochastic frontier cost function with fixed and random effects for a sample of 500 US banks and drew comparisons with other panel data models commonly used in the efficiency literature. Bos et al. (2009) report that the efficiency rankings of German savings banks are sensitive to the treatment of heterogeneity. Tecles and Tabak (2010) studied bank cost efficiency for Brazilian banks using the Bayesian stochastic frontier approach. Barros and Williams (2013) studied cost efficiency in Mexico, and Goddard et al. (2014) analyzed cost efficiency using data from banks in four Latin American countries (Argentina, Brazil, Chile, and Mexico) from 1985 to 2010.

Other papers have focused their analyses on Africa. For example, Danquah et al. (2013) measured efficiency in 133 rural and community banks in Ghana from 2006 to 2011, using financial variables such as loans (one output), deposits, and fixed assets. They concluded that true random effects and stochastic frontier models with random parameters better address unobserved heterogeneity regarding production technology, as well as in the inefficiency

[8] Technological heterogeneity can also be analyzed using the metafrontier approach based on group characteristics such as ownership and size, which in certain circumstances limit the technical choice of companies (Battese et al., 2004; O'Donnell et al., 2008). Huang et al. (2014), following Battese et al. (2004) and O'Donnell et al. (2008), proposed a two-stage metafrontier function approach to measure technical efficiency, which can be disaggregated into group-specific measures.

term. In the same region, Barros et al. (2016), following Tsionas (2002), applied a Bayesian stochastic random frontier model to banks in Angola. Their data consists of conventional financial intermediation and categorical variables to classify banks using two outputs. They found that banks belonging to conglomerates are less efficient than the rest.

3.3.2.2. Heterogeneity in output/input distance functions

An output distance function describes the degree to which a firm can expand its output vector, given an input vector. Considering that the banking industry is a multi-input and multi-output business, some studies have analyzed efficiency considering this issue in an output/input distance stochastic frontier framework. In this sense, this section shows evidence of using input or output distance functions in bank efficiency. We distinguish between papers considering heterogeneity and those which do not.

On the one hand, regarding papers which do not separate heterogeneity from efficiency, Adams et al. (1999) introduced new modeling and estimation methods to mitigate endogeneity and specification error problems. They used an output distance function to model the technology of a multi-output firm using banking industry data as an example. Furthermore, they introduced a new semiparametric method that makes minimal assumptions on the functional form of inputs in the distance function. Inui et al. (2008) investigated the pattern of changes in efficiency and productivity of the banking sectors at the firm level for 1991-2005 using the output distance function and applying the one-stage stochastic frontier approach. The study pools Japanese and Korean bank datasets to effectively compare the pattern of change between Japanese and Korean banking efficiency. Their results indicate that estimates of technical progress, technical efficiency, and total factor productivity (TFP) depend on the viewpoint about the true function of banks: the intermediation approach, the value-added approach, or the operational approach.

On the other hand, firm-specific inefficiencies can be separated from the potential technological heterogeneity among firms in the Bayesian methodology. Feng and Zhang (2014) investigated the returns to scale (RTS) of large banks in the US over the period 1997–2010 by estimating a random coefficient stochastic distance frontier model in the spirit of

Tsionas (2002) and Greene (2005). The primary advantage of this model is that its coefficients can vary across banks, thereby allowing for unobserved technology heterogeneity among large banks in the US. They found a misleading ranking of banks and mismeasurement of RTS when unobserved technological heterogeneity is not considered.

Finally, Galán et al. (2015) proposed a dynamic stochastic frontier model incorporating inefficiency specifications in a Bayesian framework. They used an unbalanced panel with data from 39 Colombian banks. Their results show high persistence in inefficiency, differences between local and foreign banks, and whether they had been merged.

3.3.2.3. Bank efficiency in Latin America and Ecuador

In Latin America, bank efficiency with SFA has also been explored by several papers. For example, Carvallo and Kasman (2005) focused on measuring cost inefficiency with a multi-output model by establishing economies of scale. In addition, they added market structure and geographic and financial depth variables. They used a panel with data from 481 Latin American banks of different types from 1995 to 2001. According to their results, smaller banks tend to be more inefficient due to undercapitalization. In another scenario, Gregoire and Ramírez Tuya (2006) analyzed cost inefficiency with single output in Peruvian microfinance institutions from 1999 to 2003, based on quantitative financial and categorical factors. Larger microfinance institutions and those participating in less concentrated markets were more efficient.

Tecles and Tabak (2010) use a Bayesian stochastic frontier to estimate cost and profit efficiency for a sample of Brazilian banks between 2000 and 2007, noting the need to compare their estimated efficiencies with those drawn from random effects models to combat heterogeneity issues. Their results indicate that large banks are more cost and profit-efficient, while some public banks are less profit-efficient. They conclude that concentration favors efficiency.

Studing Mexican banks, Barros and Williams (2013) estimated three random parameters stochastic frontier models. Mean cost efficiency was higher than that obtained from standard

panel data estimates. Goddard et al. (2014) applied SFA with a multi-output approach, using data from banks in four Latin American countries (Argentina, Brazil, Chile, and Mexico) from 1985 to 2010. They found that average efficiency estimates obtained with random parameter models tend to be higher than those obtained using fixed or random effects. Moreover, the evolution of efficiencies is variable over time and does not show a similar pattern of behavior among them. In conclusion, bank management, regulation and context have a different impact in each country, regardless of whether or not there is a crisis.

The efficiency of Ecuadorian banks has mainly been studied using non-parametric techniques such as DEA. For example, Vera-Gilces et al. (2020) studied the determinants of bank profitability utilizing a set of methodologies, including a two-stage data envelopment analysis with a fractional response model (FRM). These authors emphasize the inclusion of two variables that could affect profitability: regulation and factors derived from dollarization. In this regard, they conclude that dollarization leads to less uncertainty, thus positively influencing bank performance. In other research, Campoverde et al. (2020) examined banking efficiency through the DEA methodology. This work is interesting because it measures two periods, the first (1993-1999) before the banking crisis of 1999 when the current currency was the Sucre and the second period (2000-2018) with the US dollar as the national currency. They applied the constant return to scale (CRS) and variable return to scale (VRS) models for each period. The general conclusion is that the dollarized period reflects better efficiency under the VRS model. However, to our knowledge, no studies focus on bank efficiency measured with SFA. Proaño-Rivera and Feria-Dominguez (2023) recently used DEA and random effects panel data models. Using the second methodology, they found that the concentration of deposits and taxes mostly influences the banking industry's growth.

In this sense, our paper contributes to the literature analyzing Ecuadorian banks' efficiency in a panel data SFA context, using an output distance function to account for multi-inputs and outputs, and modeling the conditional mean of inefficiency to study determinants of inefficiency (e.g., age, bank capital reserves, ownership), some of them following regulatory reforms. To our knowledge, these aspects have not yet been studied for Ecuadorian banks.

3.4. The output translog distance function model

We use the output distance function defined in an estimable regression equation as a standard stochastic frontier model (Coelli et al., 2005; Feng and Zhang, 2014) to model the technology of a multi-input and output firm (such as a bank).[9]

The general specification for our output distance function is based on the translog stochastic production frontier model. It is a more general and flexible form for the production technology (with input and output interactions), applied by Feng and Zhang (2014) to the banking industry, Eling and Luhnen (2010) to the insurance industry, and also Assaf and Magnini (2012) and Assaf and Barros (2013) to the hotel industry. However, unlike Feng and Zhang (2014), we model technological unobserved heterogeneity and time-varying technical inefficiency, considering that the conditional mean of inefficiency depends on banking and economic factors (covariates). Then, we estimate our panel data model using a random parameters model following Tsionas (2002) and Feng and Zhang (2014) in a Bayesian approach.

The output stochastic distance translog random parameters model can be written as follows:

$$
\begin{aligned}
-\log y_{M,it} = {} & \alpha_i + \sum_{m=1}^{M-1} \gamma_{mi} \log\left(y_{m,it}/y_{M,it}\right) + \frac{1}{2}\sum_{j=1}^{M-1}\sum_{m=1}^{M-1} \gamma_{jm,i} \log\left(y_{j,it}/y_{M,it}\right)\log\left(y_{m,it}/y_{M,it}\right) \\
& + \sum_{k=1}^{K} \alpha_{ki} \log x_{k,it} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{kj,i} \log x_{k,it} \log x_{j,it} + \sum_{k=1}^{K}\sum_{m=1}^{M-1} \beta_{km,i} \log x_{k,it} \log\left(y_{m,it}/y_{M,it}\right) \\
& + \sum_{d=1}^{D} \rho_{di} \log h_{d,it} + \frac{1}{2}\sum_{d=1}^{D}\sum_{l=1}^{D} \rho_{dl,i} \log h_{d,it} \log h_{l,it} + \kappa_{1i} t + \frac{1}{2}\kappa_{2i} t^2 + \left(v_{it} + u_{it}\right) \qquad [6]
\end{aligned}
$$

[9] For the sake of brevity, we have omitted the explanation of the output distance function and the stochastic distance frontier model using the translog function. See Feng and Zhang (2014) for an overview.

where there are *M* outputs and *K* inputs, considering the linear homogeneity property of the distance function and by normalizing the distance function by one of the outputs (e.g., *M*); log is the natural logarithm; $i = 1, 2, ..., n$ is the number of banks; $t = 1, 2, ..., T_i$ is the number of periods (which could be different for each bank); y_{it} is the output of bank *i* in period *t* (where, $m = 1, ..., M$); $x_{k,it}$ is the *k*-th input for bank *i* in period *t* (where, $k = 1, ..., K$); $h_{d,it}$ is the *d*-th environmental factor included into the frontier specification $\left(d = 1, ..., D\right)$; *t* and t^2 the linear and squared time trends representing technological progress in the frontier specification; and α_i, κ_{1i}, κ_{2i}, γ_{mi}, $\gamma_{jm,i}$, $\beta_{kj,i}$, $\beta_{km,i}$, ρ_{di}, $\rho_{dl,i}$ are unknown parameters, all including the sub index *i* to accommodate the random parameters framework.

In the equation [6], the compound error $\varepsilon_{it} = v_{it} + u_{it}$ is asymmetric, where v_{it} is the idiosyncratic term, which is assumed to be i.i.d. $N\left(0, \sigma_v^2\right)$, and u_{it} is the inefficiency term, which is a non-negative and one-sided component error and it is assumed to be an i.i.d. random variable defined by the exponential distribution such as $u_{it} \sim Exp\left(\lambda_{it}^{-1}\right)$, as in Feng and Zhang (2014). However, unlike Feng and Zhang (2014), we allow that the mean inefficiency varies over time. To do this, we define its conditional exponential mean such as $\lambda_{it} = \exp\left(\phi' s_{it}\right)$, which therefore depends on a vector of exogenous variables s_{it}, and the vector of unknown parameters ϕ.

Following Feng and Zhang (2014), equation [6] can be simplified using the following general equation:

$$q_{it} = z_{it}'\theta_i + \left(v_{it} + u_{it}\right) \qquad [7]$$

where $q_{it} = -\log y_{M,it}$; z_{it}' is the vector of all variables included in equation [6] and θ_i is the vector of unknown parameters of order *L*x1 (*L*= number of total parameters). This vector can be distributed $\theta_i \sim N\left(\bar{\theta}, \Omega\right)$ and represented by the equation:

$$\theta_i = \bar{\theta} + \delta_i$$

where $\bar{\theta}$ is the mean vector of parameters and $\delta_i \sim N(0,\Omega)$, with Ω being a conformable positive definite covariance matrix. It is noteworthy that if $\delta_i = 0$, it is the fixed parameters model, where there is no technology heterogeneity.

The parameters to be estimated in our model can be expressed as $\left(\bar{\theta}, {}^{1}\!/_{\sigma_v^2}, \lambda^{-1}, \phi, \delta, \Omega\right)$, and the priors assumed for $\delta_i \sim N(0,\Omega)$, where the *j*-th element of Ω —which appears in the diagonal of Ω— is distributed as $\omega_j \sim G(1,10^{-6})$, ${}^{1}\!/_{\sigma_v^2} \sim G(0.01,0.01)$, and $\lambda_{it}^{-1} \sim G(1,0.01)$. The rest of the parameters follow a non-informative prior.

Bayesian estimation is done using expression for prior distributions, likelihood function and posterior distributions in a similar manner to Feng and Zhang (2014) (see pages 138-139 for an overview).

3.5. Empirical analysis

3.5.1. Inputs, outputs, and environmental factors

This study compiled annual accounting information from profit and loss statements from 2007 to 2017 at the end of each year, corresponding to 18 commercial banks in Ecuador. All value data in $ US are inflation-adjusted in constant 2014 $ US (i.e., we used the consumer price index of Ecuador with the base period of 2014).

In this paper, we use the profitability approach because it reflects the most efficient level of overall costs for generating profits (in $ US monetary values). It analyzes how each bank uses its resources (inputs such as operating expenses, personnel expenses, interest expenses, and loan loss provision) to generate revenues such as interest income and non-interest income from commissions. It is noteworthy that, generally, the existing literature on SFA in the

banking sector of developing countries is directed toward the production and intermediation approaches. Therefore, our proposal of the profitability approach is complementarity to the existing literature.

Based on data availability, we consider several inputs, outputs, and environmental variables in the frontier specification, all in $ US monetary values. First, we use operating expenses, personnel costs, and interest expenses as inputs (Paradi et al., 2011); among others). Second, we consider the total amount of loans, deposits, and income (interest + fees) as outputs (Cabrera-Suárez and Pérez-Rodríguez, 2021; Paradi et al., 2011; among others). Third, we consider the state-level non-performing loans (NPLs) as an undesirable output following recent banking literature (Fukuyama and Matousek, 2011; Partovi and Matousek, 2019; among others). NPLs are loans considered uncollectible according to banking standards. It is noteworthy that NPLs control for bad luck in the bank's environment (Berger and Mester (1997) but also control for extra costs associated with NPLs and/or to control for underwriting and monitoring expenditures that influence loan quality (Berger and DeYoung, 1997). In this sense, to accommodate this bad output into the model, it can also be treated as a normal input in the production function (see Halkos and Petrou, 2019).[10] Then, uncollectible accounts represent a loss of the non-recovered loan, becoming an undesirable factor in the banking process. Criteria for determining NPLs vary in the literature, depending on the length of delinquency and the probability of collecting the loans. It is worth noting that, in our case, a loan becomes non-performing when the bank considers that the borrower is unlikely to repay or when the borrower is 360 days late on a payment.[11]

Finally, we have also included other covariates in the frontier specification, such as financial capital (equity), which, following Berger and Mester (1997), is a netput to account

[10] Halkos and Petrou (2019) explain different ways which undesirable outputs can be treated in an efficiency analysis. For example, one option is to treat undesirable outputs as normal inputs in the production function. However, it is also noteworthy that authors such as Berger and Mester (1997) have used NPLs as an environmental factor into the cost/profit efficiency model.

[11] Resolution No. 209-2016-F issued by the Monetary and Financial Policy and Regulation Board of Ecuador defines uncollectible accounts as those that are more than 360 days past due. The resolution also establishes provisions based on the volume of unmatured and overdue portfolios, categorized by the number of days past due.

for banks' risk preferences. Finally, we have also included the linear and squared time trends to represent technological progress.

As environmental factors that explain time-varying inefficiency, we consider several bank determinants. For example, the number of years in business (age) is a learning-by-doing measure, and the bank's size is considered in terms of total assets. We also consider whether the bank's ownership is domestic or foreign. Finally, bank reserve requirements are considered: governments regulate banks' operations to promote sustainability and maintain user confidence, including that of savers, investors, lenders, and stockholders. We consider that they affect bank efficiency because they affect bank management, which plays an essential role in the specific objectives of the banking industry (Bansal and Singh, 2021; Dong et al., 2014; Manlagñit, 2011; Sarmiento and Galán, 2018; Vasiliou et al., 2009; among others).

Table 10 shows the mean values and standard deviation of outputs, inputs, and environmental factors. As expected, the mean of deposits is higher than the mean of loans, and the mean of income is higher than that of interest expenses. All output and input variables demonstrate a high standard deviation. This is understandable if we consider the evolution of bank intermediation (Figure 3) and the different sizes of banks. Additionally, we have incorporated a set of environmental factors to improve the explanations of technical efficiency. In this regard, we can point out that the average operating profitability (1.561%) is meager if we consider it an indicator of management performance (Altman, 1968). However, this behavior may be associated with interest rate spreads and the volume of liquidity funds. For example, the banking reserve requirements factor exhibits an average of 10.83%. This result is consistent with the Ecuadorian regulation requiring banks to deposit reserve funds with the central bank. In addition, the average number of years in business (age) is 38.54, size has a (log) mean of 19.73, and foreign is a dummy variable indicating that only 5.64% of banks in the sample are foreign.

Table 10. Descriptive statistics of inputs, outputs, and environmental factors.

Variable	Name	Mean	Standard deviation
Outputs			
y_1	Loans ($ US.)	831,142	1,262,793
y_2	Deposits ($ US.)	1,193,917	1,676,367
y_3	Income (interest + fees) ($ US)	89,123	141,138
Inputs			
x_1	Operating expenses ($ US.)	49,713	83,145
x_2	Personnel expenses ($ US.)	22,700	31,345
x_3	Interest expenses ($ US.)	22,351	29,877
x_4	Non-performing loans ($ US.)	3,361	6,398
Environmental factors in the frontier			
h_1	Financial capital	145,219	203,417
Environmental factors in the inefficiency term			
Age	Number of years in business	38.544	24.604
Size	Total assets (natural log)	19.8866	1.8269
Operating profitability	Ratio: Earnings Before Interest and Taxes / total assets	0.0156	0.0153
Bank reserve requirements	Ratio: Central bank reserve requirements / Annual balance of deposits	0.10827	0.0980
Foreign	=1 if foreign bank; =0, otherwise	5.641%	--

Notes: Descriptive statistics are reported for the pooled sample. All monetary values are in millions of $ US.

3.5.2. Efficiency estimates

We have estimated the translog output distance stochastic frontier model defined by equation [1]. It should be noted that distance functions (like the production functions) suffer from an inherent endogeneity problem if inputs or outputs are endogenous to the firm's decision-making (Tsionas et al., 2015). However, the bias is not a problem in an output distance function that uses a translog functional form (Coelli and Perelman, 2000; Johnes, 2014; Letti et al., 2022).

Results appear in Table 11. However, we should highlight some issues. First, to evaluate the merits of our preferred specification, we compare our model with several specifications,

such as in Barros and Williams (2013) and Goddard et al. (2014). Therefore, our study explores three Bayesian perspectives of equation [7]: the standard fixed parameters model, widely employed in stochastic frontier literature (e.g., Koop and Steel, 2001; O'Donnell and Coelli, 2005); the random constant model (we named RPM (constant) and which is similar to the true-random model of Greene (2005)); and a more general random parameter model with constant and input coefficients being random, which accounts for individual-specific unobserved heterogeneity across all inputs (we called this RPM (constant and inputs). Notably, we have estimated equation [7] including all input, output and environmental variables and their cross-terms for greater flexibility. However, there is a high sensibility to the different specifications we have used and the inclusion of some variables, besides problems of estimation convergence. Therefore, Table 3 only shows those model results where the specification converged in the estimation process. This aspect implied that some equation [6] variables were not used in the estimation.

Second, we assign the same prior distributions to the common parameters in all models to ensure comparability. In general, we assume a prior normal distribution with a mean of 0 and a sufficiently large variance to capture uncertainty for all the parameters in expression [7], similar to Tsionas (2002) and Feng and Zhang (2014). However, to satisfy the monotonicity conditions of the output distance function, as indicated by O'Donnell and Coelli (2005) and Feng and Zhang (2014), we need to impose $\gamma_m \geq 0$ and $\alpha_k \leq 0$. Here, we incorporate flat gamma prior distributions, with parameters 1 and 10^{-3}, for these parameters to meet these conditions, as in Kerman (2011). On the other hand, we assume that the prior of v is independently and identically distributed (i.i.d.) as $N\left(0, 1/\sigma_v\right)$, where $1/\sigma_v$ follows a Gamma distribution with shape and scale parameters equal to 0.01. Additionally, the inefficiency term is assumed to be an i.i.d. random variable defined by the exponential distribution, where the parameters of the conditional mean inefficiency follow non-informative priors.

The second and third Bayesian models incorporate constant and constant input and environmental parameters specific to each bank, respectively. For example, by decomposing

input parameters into its average vector, $\bar{\alpha}_{ki}$, and a random vector δ_i, we can express $\alpha_{ki} = \bar{\alpha}_{ki} + \delta_i$, where $\bar{\alpha}_{ki} \sim N\left(0, 1/\sigma\right)$, with $1/\sigma = 10^6$ and $\delta_i \sim N\left(0, 1/\sigma_{\delta_i}\right)$ and $\sigma_{\delta_i} \sim G(0.01, 0.01)$. Similarly, the same assumptions are considered for coefficients of environmental variables in the frontier specification.

Third, we consider the inclusion of several covariates into the conditional mean inefficiency equation based on the exponential to obtain time-varying inefficiencies. Mainly, we include environmental factors such as age, operating profitability, size, banking reserve requirements, and a dummy variable that represents foreign ownership of the bank. Other variables, such as time and its quadratic term, were also used in the mean inefficiency model. However, their inclusion provoked convergence problems in our estimations. Therefore, we cannot account for (as other papers do) the estimation of inefficiency change and catch-up with best practices.

Fourth, Table 11 includes mean parameter estimates and their standard deviations, the logarithm of likelihood, and the descriptive statistics for the efficiency estimates calculated by the Jondrow et al. (1982) estimator (JMLS) considering that $\varepsilon_{it} = v_{it} + u_{it}$. Estimation was done using WINBUGS, where the posterior estimates were obtained, carrying out 200,000 iterations for each sample after a burn-in of 100,000 simulations. It is also noteworthy that the monotonicity conditions for all inputs and outputs hold. For example, they were calculated as the derivative of the output distance function regarding inputs, and are negative in median terms. In the case of outputs, they were positive.

Based on estimation results in Table 11 and the deviation information criteria (DIC)—which is extensively used in Bayesian model selection problems and where models with smaller DIC are preferred to models with larger DIC (Spiegelhalter et al., 2002)—the RPM (constant) is preferred to both the fixed parameters and random constant and inputs parameter models. Therefore, we chose RPM (constant) to interpret the results.

Table 11. Bayesian panel data estimates from the translog output distance stochastic frontier model with covariates in the frontier specification and mean inefficiency using an exponential distribution with profitability approach.

	Fixed parameters model		RPM (constant)		RPM (constant and inputs)	
Variables	**Mean coefficient**	**Standard deviation**	**Mean coefficient**	**Standard deviation**	**Mean coefficient**	**Standard deviation**
Translog stochastic frontier						
$\log y_1/y_3$	0.023**	0.021	0.054**	0.045	0.035**	0.032
$\log y_2/y_3$	0.077**	0.061	0.075**	0.069	0.097**	0.083
$(\log (y_2/y_3))^2$	0.131**	0.029	0.159**	0.042	0.097**	0.045
$\log x_1$	-0.874**	0.023	-1.307***	0.000	-1.554**	0.061
$\log x_2$	-0.249**	0.031	-0.807***	0.013	-0.047**	0.032
$\log x_3$	-0.335**	0.063	-0.139**	0.017	-2.207**	0.028
$\log x_4$	-0.234**	0.060	-0.392**	0.031	-0.221**	0.076
$(\log x_1)^2$	0.013**	0.004	0.015**	0.006	0.042***	0.003
$(\log x_2)^2$	-0.021**	0.004	-0.021***	0.001	0.172***	0.004
$(\log x_3)^2$	0.016**	0.004	-0.008**	0.002	- 0.814***	0.004
$(\log x_4)^2$	0.011**	0.004	0.026**	0.002	0.111**	0.011
$\log x_1 \times \log x_2$	0.011**	0.003	0.052***	0.001	0.108***	0.002
time	-0.022	0.017	-0.039**	0.011	0.015	0.016
$time^2$	0.002	0.003	0.002	0.001	-0.003	0.002
Constant	3.845**	0.286	--	--	--	--
Mean inefficiency						
Age	-0.147	0.388	-0.072	0.153	0.487	0.340
Operating profitability	1.894	1.123	0.974	0.808	0.778	1.235
Size	1.871**	0.356	0.531**	0.166	0.578**	0.335
Bank reserve requirements	2.983**	0.681	0.605	0.636	-1.612	0.975
Foreign	-0.537	0.778	-5.316***	0.351	-2.402**	0.490
Constant	2.952**	0.471	2.071***	0.155	2.340***	0.343
DIC	-129.1		-412.1		-348.0	
Descriptive statistics for efficiency JLMS estimates:						
Mean	0.899		0.837		0.871	
Standard deviation	0.156		0.221		0.190	
Median	0.968		0.916		0.943	
Minimum	0.328		0.020		0.031	
Maximum	0.998		0.983		0.996	
Number of banks	18		18		18	
Total panel observations	193		193		193	

Notes: ***, **, * indicate significance at 1%, 5%, 10% level, respectively. DIC is the deviation information criterion. Total panel observations are the number of effective data used in the estimations.

In general, RPM (constant) with covariates into the conditional mean of inefficiency term results indicate that parameters for inputs and outputs are statistically significant, but some

refer to environmental variables.12 It suggests that there is time-varying inefficiency and unobserved heterogeneity. Also, descriptive statistics for time-varying efficiency based on the JLMS estimates vary between 2% and 98.3%. These results show high variation between banks. However, the efficiency is 83.7% in mean terms, indicating that banks can improve efficiency by 16.3% with a better allocation of their inputs. In median terms, the improvement is around 8.4% (i.e., (1-0.916) × 100).

3.5.2.1. Environmental factors affecting inefficiency

Our results show that a few environmental factors influence bank efficiency in Ecuador. For example, a statistically significant factor is the bank's ownership (foreign). Its coefficient is statistically significant at the 5% significance level, and it is negative, which means that domestic banks are more inefficient than foreign ones. Foreign bank penetration is expected to stimulate improvements in regulation and accounting standards (Clarke et al., 2003). The efficiency of foreign bank subsidiaries could be adversely affected by operating diseconomies of distance from the home country (see Berger et al. (2005). Our finding is similar to Barros et al. (2016) and Shanmugam and Das (2004), who found foreign banks to be more efficient than domestic banks, contrary to Tahir and Haron (2008) and Vernikov and Mamonov (2018). Nevertheless, the domestic banks could see this highlight as an opportunity to implement innovative products and services to improve competitiveness.

Governments regulate banks' operations in most countries to promote sustainability and maintain user confidence, including that of savers, investors, lenders, and stockholders. Therefore, there is a connection between regulation and bank management to improve the banking system's efficiency (Huhtilainen, 2019). For example, Kashyap and Stein (1994) argued that reserve requirements could improve bank efficiency by reducing the risk of bank failures and financial crises. They suggested that reserve requirements can help banks have enough liquidity to meet their obligations and withstand unexpected shocks, improving their efficiency. However, the bank reserve requirements that reflect banks' obligation to form a

[12] It is noteworthy that financial capital was included as a netput to account for banks' risk preferences into the three models, but unfortunately, its inclusion provoked estimation and convergence problems.

reserve fund deposited at the Central Bank is not an essential factor explaining Ecuadorian bank inefficiency because, although it is positive, it is not statistically significant.

Our results for Ecuadorian banks are different to the empirical literature, which has analyzed the impact of banking sector restructuring and regulatory reforms to improve sector competition and risk-taking on bank efficiency (Barros and Williams, 2013; Berger and Bonaccorsi Di Patti, 2006; Chortareas, Girardone, et al., 2012; Pessarossi and Weill, 2015; Proença et al., 2023; among others). In general, this literature has found varied results concerning the effect of regulation. For example, Berger and Bonaccorsi Di Patti (2006) showed that capital ratios negatively affected efficiency, while Pessarossi and Weill (2015) pointed out that they have a positive effect. Fiordelisi et al. (2011) found that the less efficient banks tend to take on more risk and that better-capitalized banks perform better in terms of efficiency analyzing efficiencies of cost, revenue, and profit. On the other hand, Chortareas et al. (2012) and Lee and Chih (2013) suggested that stringent regulation adversely affects bank efficiency despite enhancing stability.

Other variables such as operating profitability and age, are irrelevant to banking inefficiency in Ecuador in the analyzed period. For example, we can observe that the coefficient of age variable is negative and not statistically significant. Other studies, such as that of Stewart et al. (2016) in Vietnamese banks, found that age significantly and negatively impacts bank efficiency. Also, the study conducted by Achi (2021) on Algerian banks found a negative and significant influence on the efficiency of the profitability dimension. Although inference leads to the assumption that banks with fewer years in operation would be more efficient, we consider our result inconclusive. The operating profitability variable is not statistically significant but shows a positive coefficient. However, Fernandes et al. (2018) found a positive and significant correlation with efficiency in European banks although they explained that European banks took greater credit risk than they hedged with unlimited access to long-term central bank funding. In contrast, Ecuadorian regulation requires larger liquid reserve funds.

Finally, the coefficient of size is statistically significant and positive, indicating that increasing size increases inefficiency. This conclusion disagrees with the finding of Jiménez-

Hernandez et al. (2019) in several Latin American countries (including Ecuador), who estimated that size has a positive relationship with efficiency, in the same direction that Perera et al. (2008) found in South Asian banking. According to Tabak et al. (2012), larger banks demonstrate better conditions to manage the relationship between market competition and risk taken to improve market share. However, Bhuyan et al. (2021) found a negative relationship between size and efficiency in Indian banks. They argued that large banks may be less productive due to diseconomies of scale caused by low-cost product diversity.

3.5.2.2. Overall estimated density and time-varying efficiency distributions

Regarding the JLMS measures (Jondrow et al., 1982), Figure 4 shows the estimated kernel density for the transient efficiencies (posterior expected technical efficiency) and the time path of the production (boxplot) distributions using the profitability approach, respectively.

Figure 4. Estimated density for the transient and boxplot efficiencies per year using the RPM (constant).

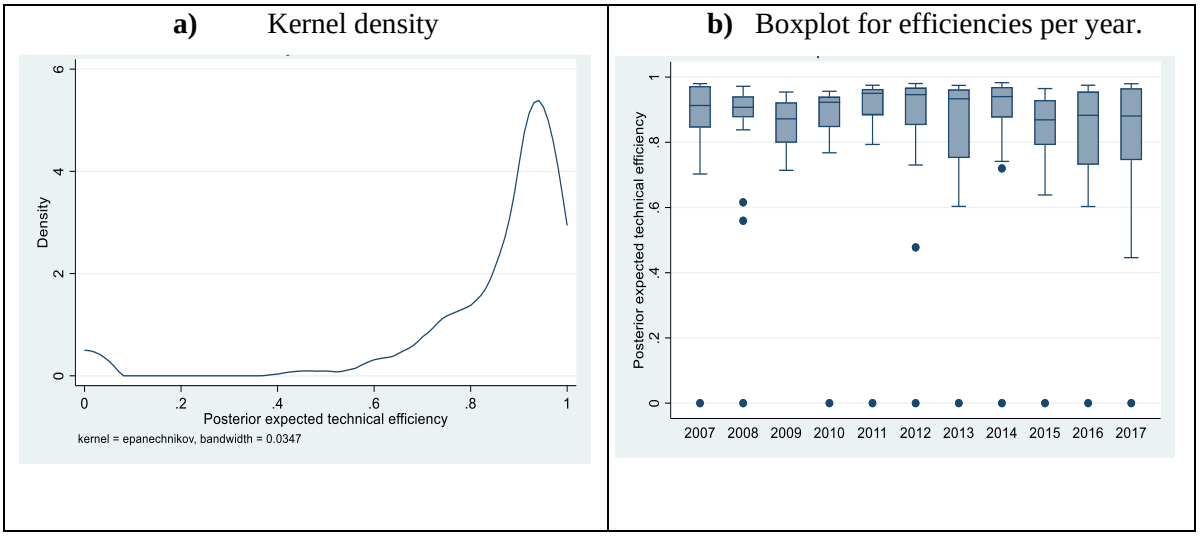


Figure 4a shows that the distribution is skewed to the left, as expected. Figure 4b shows the year-by-year boxplot for estimated efficiencies over time. In this case, as can be seen, transient efficiency tended to be (slightly) constant over time in median terms from 2007 to

2017. It shows less dispersion above the median than the lower quartiles, which reflects the wider distribution and some outliers. Interestingly, the estimated efficiencies above the median in the period studied tend to be constant, except between 2008-2010 and 2015. Therefore, the banking system demonstrates its capacity to react to possible shocks, as evidenced in the years of 2008-2010. We can say in general terms that these 18 commercial banks managed their efficiency acceptably.

3.5.2.3. Returns to scale

The production technology can exhibit increasing, decreasing, or constant (RTS), indicating the proportionality or not of changes in output after the quantities of all inputs in production have been changed by the same factor.

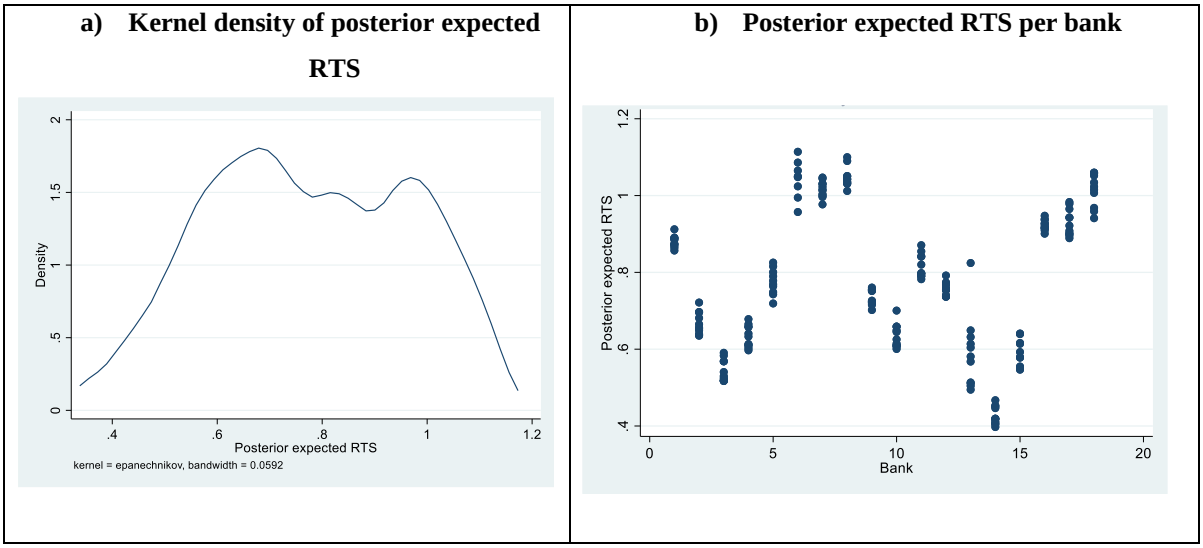
We calculate an RTS measure using the expression for the output distance function in Feng and Zhang (2014) and evaluate it in our model estimates (equation [1]) based on the exponential case for inefficiency. Figure 5 shows the posterior expected distribution of RTS for all banks and years and the posterior expected RTS estimates for each bank, both for the RPM (constant).

As we can observe, Figure 5a depicts a bimodal distribution for posterior expected RTS using all data for the period 2007-2017, but the modes are lower than 1. The first mode is 0.65, and the second mode is 0.98. In this sense, our results show the presence of two groups of banks. On the one hand, most banks in Ecuador (first mode) exhibit decreasing RTS (RTS<1) during the overall period. Hence, it implies that a decrease in production factors leads to a disproportionate decrease in output. On the other hand, the second group shows banks exhibiting RTS close to 1 (operating at a scale close to their optimum size) and then constant RTS (RTS=1). It is noteworthy that if we analyze RTS by bank (Figure 5b), RTS>1 for a few banks and some periods, being greater than one only for one bank.

These results do not suggest that banks of different sizes (in total assets) tend to have different levels of RTS. In this sense, we regress estimated RTS on a constant, size and squared size for all the periods using a panel data random-effects GLS regression. The R^2 is

0.97, and the estimated coefficients are 0.79 (constant), -0.19 (size) and -0.03 (squared size), respectively. They are statistically significant at any significance level (p-value=0.00, in all cases). These results generally indicate a clear negative pattern for size with a decreasing rate (e.g., the coefficient for size is negative, and for squared size is also negative). Therefore, increasing the size decreases RTS. This finding does not match the commonly found pattern concerning the relationship between asset size and RTS. However, Feng and Zhang (2014) also found results differing from the common empirical pattern. They have pointed out that technology heterogeneity could explain this discrepancy.[13]

Figure 5. The posterior expected of the estimated RTS for the overall period and each bank using the RPM (constant).



[13] Feng and Zhang (2014) have pointed out that when technology is heterogeneous, it is possible to have two banks of different sizes, where the smaller one shows decreasing returns to scale (e.g., banks operating at a scale greater than its own optimum size) and the larger one shows increasing returns to scale (e.g., banks operating at a scale smaller than its own optimum size). Therefore, the relationship between returns to scale and asset size is no longer independent of the technologies employed, and the pattern commonly found in relation to the relationship between returns to scale and asset size does not necessarily hold for banks that use different technologies.

Chapter 4. Assessing the effects of loan loss provisions and non-performing loans in bank's inefficiency

4.1. Introduction

Deregulation, globalization, financial innovation, and technological progress have gradually reduced the costs of information processing and transmission and have been major forces impacting the performance of the international banking sector (Girardone et al., 2007).

The quality of banks' assets can affect their efficiency and stability. Besides, it is a relevant indicator of signs of bankruptcy. The unsustainable volume of loan losses since 2007 remained an important factor that negatively affected bank performance in Western countries, reducing operating profit and affecting efficiency. During the 2008 financial crisis, it became clear that the flexible banking supervision and regulation applied in developed countries were insufficient to moderate the decisions of some bank managers to take excessive risks (Herring and Calomiris, 2012).

In general, the regulatory response to that crisis was to introduce differentiation in loan loss provisions, loan restructuring rules, and the rescue of troubled banks (Partovi and Matousek, 2019). Regulators required banks to hold enough capital to absorb losses and to limit moral hazard behavior (Pessarossi and Weill, 2015). For example, loan loss provisioning helps ensure that banks are adequately protected against credit losses, anticipating the possible loss to control the credit risk. In accounting terms, loan loss provisioning is an income statement expense set aside to cover losses such as non-performing loans (NPLs, bad loans), customer bankruptcy, and renegotiated loans that incur lower payments than previously estimated.[14] Therefore, banks

[14] In general, loan loss provisions are then added to the loan loss reserves; a balance sheet item that represents the total amount of loan losses subtracted from a company's loans. On the other hand, a loan becomes non-performing when the bank considers that the borrower is unlikely to repay.

need to keep a close eye on the loans they have made, quickly identify those loans at risk of becoming delinquent, and classify them accordingly. Still limiting the profitability of their resources and the possibilities of growth, the role of loan loss provisions cannot be ignored in bank efficiency studies as additional or alternative inputs/outputs or explanatory factors of efficiency.

To our knowledge, in the empirical banking efficiency literature, capital requirements have been analyzed as determinants of efficiency using capital ratios. Although a few papers are investigating such issues, some results indicate that capital ratios positively affect cost efficiency (see Pessarossi and Weill, 2015). But provisioning has also been used in empirical works. For example, loan loss provisions have been included as an input using intermediary and profitability approaches (see Paradi et al., 2011). However, they have not yet been used as an undesirable output. It is worth noting that the role of NPLs, as a part of loan loss provisions, has been studied in bank efficiency by considering that they are an undesirable output. In this sense, it allows for a simultaneous expansion of the bank's desirable outputs and contraction of NPLs (as an undesirable output) using both the non-parametric models (e.g., Barros et al., 2012; Fukuyama and Matousek, 2011; and Partovi and Matousek, 2019) and parametric (stochastic frontier) models (G. A. Assaf et al., 2013). In general, results indicated a negative impact of NPLs on efficiency.

The main contribution of this chapter to current research on the efficiency of banks is analyzing the effects of the amount of capital or accounting requirements using loan loss provisions as bad output, but also comparing their effect with the NPLs. The reasons are varied. On the one hand, both are interesting measures that derive from the specific banking regulation for possible loan losses and the accounting treatment of uncollected loans. They can affect bank efficiency differently for two motives. First, NPLs reduce banks' earnings and cause losses, provoking a reduction in bank efficiency. Second, by booking a provision, the bank takes a loss reducing its capital by the amount of money it will not be able to collect from the client (it means that the bank recognizes a loss on long delinquent loans). Therefore, NPLs become a more undesirable factor than LLPs in the bank intermediation process. Henceforth, the effect of NPLs on bank inefficiency could be higher than the effect of loan loss provisions. On the other hand, this analysis could be important for bank staff, clarifying policy issues and enabling bank managers to identify strengths and weaknesses in their operations using these alternative (bad) outputs. It could promote strategies to minimize inefficiencies in bank operations by highlighting deviations from a "best practice" unit for any scale or product mix.

For these motives, we evaluate the effect of banking regulation on the production of services, including loan loss provisions as a bad output. Then, we compare their effects on inefficiency against NPLs and assess if they could under- or overestimate bank efficiency.

We will focus on a two-step procedure. First, we calculate the banks' efficiency using the non-radial data envelopment analysis (DEA) methodology. Particularly, we use the slacks-based measure (SBM) dealing with undesirable outputs (Tone, 2003) to calculate efficiency in the first step. Then, in the second step, we assess some economic factors affecting bank efficiency used in the empirical literature.

Our empirical research focuses on the Ecuadorian banking industry as a case study. Banking regulation is relevant in emerging countries because they are more exposed to global financial shocks. Ecuador's banking system has been profoundly restructured since the 1999 banking crisis, severely impacting the national economy and financial institutions. It led the government to dollarize the economy in 2000, replacing the Sucre, the national currency. This currency transition, accompanied by political turbulence, brought reforms aimed at correcting the deficiencies exhibited in the past and improving control of the banking system. In 2007, the change of government regime, which continued until 2017, generated a period of political stability in Ecuador. One of the fundamental pillars of economic policy was the efficient control of the national financial system. Therefore, it is interesting to investigate the banking efficiency within this period of political stability and reforms to the financial system.

The rest of this chapter is structured as follows: Section 4.2 briefly outlines the Ecuadorian bank industry. It continues with Section 4.3, describing the literature on bank efficiency and the use of NPLs as undesirable outputs. Section 4.4 shows the use of SBM models with separate outputs to determine bank efficiency. Section 4.5 presents the data and the empirical results. Finally, the main conclusions drawn are in Section 4.6.

4.2. Ecuador's bank industry, loan loss provisions and NPLs

After a period of adaptation to dollarization (2000-2006), accompanied by increased regulations for the banking system (Quispe-Agnoli and Whisler, 1998), the government regime in Ecuador during 2007-2017 promoted policies to improve bank deepening (Vera-Gilces et al., 2020). In this context, the Central Bank deepened the regulation of bank interest rates. In this scenario, the intermediation margin was reduced, forcing the increase of deposit and placement operations to improve the banking system's sustainability and profitability. As a result,

financing from the banking system evolved favorably during this period, significantly improving the volume of deposits and loans[15] (Torres Cumbicus, 2020). However, there are intrinsic processes and factors to banking intermediation that lead to the relaxation of regulation or deregulation (Unda and Margret, 2015).

Among other effects, Baltensperger and Dermine (1986) point out that banking regulation provides certainty for ensuring the preservation of savings through risk rating processes for banks and borrowers. In addition, it promotes the increase in equity participation based on the volume of intermediation. It motivates shareholders not to consider equity as a real option for bankruptcy but rather to strive to increase its value. For example, in Ecuador, banks must maintain liquid capital funds representing an average of 10% of the current balance of the loan portfolio to guarantee depositors' withdrawals (Weisbrot et al., 2013). Other measures, such as loan loss provisions (LLPs), underpin the regulation's purpose concerning improving the primary participants' confidence as savers and shareholders.

For financial institutions, LLPs are a mandatory way to improve solvency and recognize losses generated by uncollectible accounts (Park and Weber, 2006). The rules for forming LLPs are associated with the quality of the loans granted and the time in default. The longer the period of delinquency, the higher the provision percentage. This mechanism allows the volume of provisions to be variable. Loan loss provisions are significant for shareholders because their application reduces operating earnings, affecting equity.

On the other hand, the banks' accounting records uncollectible accounts, despite the rigorous conditions and restrictions on borrowers. The occurrence of uncollectible accounts is covered in the first instance by LLPs, protecting savers and penalizing shareholders. Logically, bank management is driven to improve collection controls. A loan becomes non-performing when the bank considers that the borrower is unlikely to repay or when the borrower is 360 days late on a payment.[16] Therefore, uncollectible accounts, if they occur, represent a loss of the non-recovered loan, becoming an undesirable factor in the banking process.

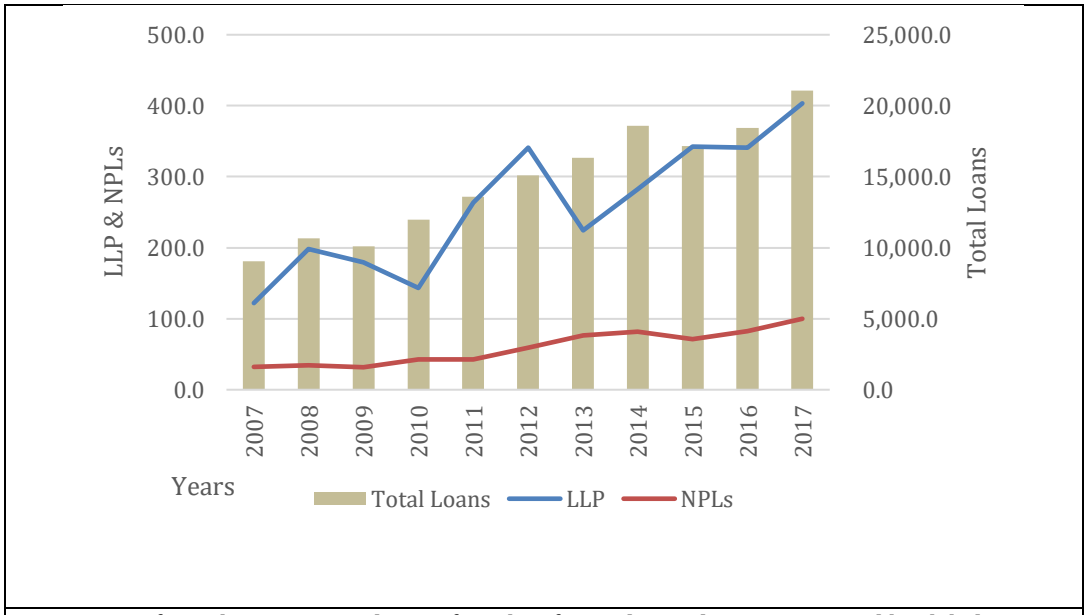
[15] The volume of the total loan portfolio went from 20% in 2007 to 39% in 2019 with respect to GDP. This indicator includes private banks, financial companies, mutual societies, cooperatives, and development banks (Torres Cumbicus, 2020).

[16] The Monetary and Financial Policy and Regulation Board of Ecuador establishes in Resolution No. 209-2016-F that accounts more than 360 days past due are considered uncollectible. In addition, the same document establishes the formation of provisions based on the volume of the unmatured portfolio and the overdue portfolio according to the number of days past due.

Consequently, among the aspects covered by this study, some regulation factors influencing banking efficiency: income due to the control of interest rates, loans granted due to credit risk control, savers' deposits due to the certainty that banking represents, and provisions for uncollectible accounts due to the obligation to maintain them at a level associated with current loans.

Figure 6 shows the evolution of LLPs and non-performing loans NPLs relative to total loans.

Figure 6. Loan Loss Provisions and Non-Performing Loans.



Notes: Data from the Superintendence of Banks of Ecuador. Values are year-end book balances in millions, adjusted to constant 2014 prices.

Banking regulation requires banks to maintain certain levels of LLPs and controls the terms on which non-performing loans must be accounted for as NPLs. These variables are expected to increase over time due to the increase in total loans. However, LLPs are notably higher than NPLs, highlighting that LLPs cover between three to four times the amount of NPLs. The variability of LLPs as a proportion of total loans stems from the composition of the past-due portfolio and the mix of delinquency terms. On the other hand, the volume of NPLs is directly generated by non-performing loans each year. From another point of view, from 2007 to 2017, NPLs grew 210%, LLPs 230%, and total loans 133%. It means that banks formed more provisions due to higher NPLs, and higher NPLs as a proportion of total loans.

In Ecuador, empirical quantitative or qualitative research on banking is scarce. Some recent studies have shown the behavior of Ecuadorian banking. For example, Campoverde Campoverde et al. (2020) investigated the efficiency of Ecuadorian banking using the DEA

methodology. This work compares pre-dollarization (1993-1999) and post-dollarization (2000-2018). The results generally indicate that the post-dollarization period is more efficient than the pre-dollarization period. In addition, large banks tend to be more efficient than medium and small banks. Another motivating research on the Ecuadorian banking system was carried out by Vera-Gilces et al. (2020). These authors used a set of quantitative methodologies to analyze the evolution of bank profitability. For this purpose, they formulated an efficiency index using the two-stage DEA methodology through a fractional response model. This index is part of the determinants of bank profitability. However, no papers are investigating the effects of LLPs and NPLs on Ecuador's banking industry.

4.3. Bank efficiency and undesirable outputs

The literature on banking efficiency is extensive (see Berger and Humphrey, 1997, and Fethi and Pasiouras, 2010, for two excellent surveys), covering numerous countries and regions worldwide (North America, Europe, Asia-Pacific, and Oceania). The research on this topic uses several econometric approaches based on parametric and non-parametric models.

Generally, the inputs and outputs chosen to estimate technical or cost efficiencies are non-negative in most bank studies. However, the theoretical literature on efficiency in a non-parametric framework allows us to use several other categories of inputs and outputs, such as undesirable (bad) inputs or outputs[17] or negative (but desirable) inputs or outputs, which are not bad in themselves.

The literature has shown that researchers can vary the treatment of undesirable outputs in efficiency modeling. For example, one option is as normal inputs in the production function (G. Halkos and Petrou, 2019). In the empirical banking literature, loan losses have been considered an input in the intermediation and profitability dimensions (Paradi et al., 2011, page 103).[18] Efficiency models can include this variable to compensate or penalize banks with risky credit behavior (for example, poor credit decisions or accepting riskier clients) (Paradi et al., 2011). In general, the joint research on efficiency uses the classic DEA models.

[17] In general, undesirable products are derived from production activities. For example, production often generates harmful by-products that are discharged into the environment, such as pollution, waste, noise, among others.

[18] Efficiency of banks and branches can be analyzed applying different approaches such as production, intermediation and profitability approaches using both non-parametric and/or parametric stochastic frontier methods (Paradi et al., 2011).

There are other considerations regarding using bad loans as a bad output. To the authors' knowledge, non-performing loans have been used as an undesirable output in several empirical papers (e.g., Barros et al., 2012; Fukuyama and Weber, 2008, 2015; Park and Weber, 2006; Partovi and Matousek, 2019; among others),[19] but not LLPs.

There are several methods for addressing undesirable outputs in a non-parametric efficiency framework (see Allen, 1999; Dyckhoff and Allen, 2001; or Halkos and Petrou, 2019; for a general overview). For example, undesirable outputs can be treated with the SBM approach (Tone, 2003) or the directional distance function (first proposed by Chung et al., 1997). In the latter case, directional distance functions have been used in bank efficiency studies employing NPLs as undesirable outputs. For example, Fukuyama and Weber (2008) developed a network two-stage system model with bad outputs based on Tone's (2001) SBM extension into a directional distance model. They examined bank efficiency and shadow prices for NPLs for Japanese commercial banks in 2002-2004 and concluded that NPLs should not be ignored in the case of Japanese banks. Other authors used a non-radial directional performance measurement that quantified the impact of an undesirable output as NPLs, as Barros et al. (2012) did in Japanese banks. Some results indicated that NPLs remain a significant burden for banks' performance and that banks' inputs must be utilized more efficiently, mainly labor and premises, among other conclusions. Finally, Partovi and Matousek (2019) studied technical and allocative efficiencies in Turkish banks from December 2002 to December 2017. They considered the assumption of constant returns to scale and applied a directional distance model to provide efficiency estimates, also focusing on NPLs as an undesirable output. Then, these authors analyzed the efficiency factors by applying quantile regressions to panel data. Their results support the thesis that NPLs negatively impact technical efficiency, confirming the banking sector's "bad management" hypothesis.

More recently, Shi et al. (2021) analyzed the efficiency of 16 publicly listed Chinese commercial banks in the 2012–2016 period. They utilized the SBM-Network DEA (NDEA) model with a multi-stage process connected serially and in parallel. In this work, the authors used the deposits factor as an intermediate input and NPLs as an undesirable output.

All the above studies provide evidence that NPLs contribute to bank inefficiency. However, they do not study the effect of LLPs on efficiency.

[19] The importance of NPLs has been discussed by Mester (1996) and Berger and DeYoung (1997), while many studies have found that NPLs negatively affect banks' efficiency and stability because they deteriorate the quality of assets in a bank.

4.4. SBM models

Let *n* be observations of banks (or, in general, decision-making units, DMUs), $j = 1, 2, ..., n$. Let x_{ij} be the observed level of the *i*-th input at DMU *j* and let $x = \left(x_{1j}, ..., x_{kj} \right) \in \Re_+^k$ be the vector of *k* inputs for the *i*-th unit; y_{rj} is the observed level of the *r*-th output at DMU *j*, where $y = \left(y_{1j}, ..., y_{mj} \right) \in \Re_+^m$ is a vector of *m* outputs. Technology is defined as $T = \left\{ (x, y) : x \, can \, produce \, y \right\}$, and the input requirements and output sets are defined as $L(y) = \left\{ x : (x, y) \in T \right\}$, $y \in \Re_+^m$ and $P(x) = \left\{ y : (x, y) \in T \right\}$, $x \in \Re_+^k$, respectively. Let ϕ and γ be the radial efficiency scores (a value between 0 and 1), ρ the non-radial efficiency score, λ_j the optimal weights of the referenced units for unit *j*, s_i^- the input slack/excess for the *i*-th input, and s_r^+ the output slack/shortfall for the *r*-th output.

Considering desirable (good) and undesirable (bad) outputs, we can separate y_{rj} in the following way: y_{rj}^g is the observed level of the *r*-th output at DMU *j* corresponding to good outputs, where $y^g = \left(y_{1j}^g, ..., y_{mj}^g \right) \in \Re_+^{m_1}$ is a vector of m_1 good outputs, and y_{rj}^b is the observed level of the *r*-th output at DMU *j* corresponding to bad outputs, where $y^b = \left(y_{1j}^b, ..., y_{mj}^b \right) \in \Re_+^{m_2}$ is a vector of m_2 bad outputs. Also, s_r^g is the output slack/shortfall for the *r*-th good output, and s_r^b is the output slack/excess for the *r*-th bad output.

DEA uses radial or non-radial measures to evaluate the efficiency of DMUs (Ashrafi et al., 2013). The assumption for radial models is that there is a proportional change of inputs or outputs, and they usually disregard the slacks in the efficiency scores. The non-radial measures consider the slacks of each input and output and allow for the variations of both inputs and outputs, which are non-proportional. Since the classic DEA models (e.g., CCR (Charnes et al., 1978) and BCC (Banker et al., 1984)) do not consider the effect of slacks of inputs and outputs on the reliability of model estimation, their efficiency evaluations can have significant deviations (Deng et al., 2020).

Next, we briefly explain SBM models distinguishing the inclusion of undesirable outputs.

4.4.1. SBM model with desirable inputs and outputs

Tone (2001) recommended using the SBM model based on slacks to evaluate the relative efficiency of DMUs. The SBM model based on VRS technology can be written as follows:

$$\rho^* = \min_{\rho,\lambda} \rho = \frac{1-\frac{1}{k}\sum_{i=1}^{k}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{m}\sum_{r=1}^{m}\frac{s_r^+}{y_{r0}}}$$

subject to:

$$\begin{aligned} & y_{r0} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \\ & x_{i0} - \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = 0 \\ & \sum_{j=1}^{n} \lambda_j = 1 \\ & \lambda_j, s_i^-, s_r^+ \geq 0, \forall j, i, r \end{aligned} \qquad [8]$$

The optimal ρ^* is the efficiency of the SBM model $0 \leq \rho^* \leq 1$. If $\rho^* = 1$ DMU is fully efficient, because $s_i^- = s_i^+ = 0$, while $0 \leq \rho^* < 1$ the DMU is inefficient.

4.4.2. SBM model with separable bad outputs

Tone (2003) formulated the SBM model considering separating undesirable or bad outputs from good outputs. The SBM model with separate bad outputs based on VRS technology can be written as follows:

$$\rho^* = \min_{\rho,\lambda} \rho = \frac{1 - \frac{1}{k}\sum_{i=1}^{k} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{(m_1 + m_2)}\left(\sum_{r=1}^{m_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{m_2} \frac{s_r^b}{y_{r0}^b}\right)}$$

subject to:

$$\begin{aligned} y_{r0}^g &= \sum_{j=1}^{n} y_{rj}^g \lambda_j - s_r^g \\ y_{r0}^b &= \sum_{j=1}^{n} y_{rj}^b \lambda_j + s_r^b \\ x_{i0} &- \sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- = 0 \\ &\sum_{j=1}^{n} \lambda_j = 1 \\ &\lambda_j, s_i^-, s_r^g, s_r^b \geq 0, \forall j, i, r \end{aligned} \qquad [9]$$

The optimal ρ^* is the efficiency of the SBM model $0 \leq \rho^* \leq 1$. If $\rho^* = 1$ DMU is fully efficient, because $s_i^- = s_i^g = s_i^b = 0$, while $0 \leq \rho^* < 1$ the DMU is inefficient.

4.5. Empirical analysis

4.5.1. Data

In this study, annual accounting information was compiled from financial statements from 2007 to 2017, corresponding to 18 commercial banks in Ecuador. Next, we describe the factors used to assess efficiency under the DEA-SBM approach, followed by determinants used in the second step.

Inputs and outputs

Generally, our inputs and outputs are frequently found in the literature review. As good outputs, we have included the gross income, which includes gained interest income from loans and money investments, and non-interest income earned as service commissions and others (Meslier et al., 2014; Osuagwu et al., 2018). Deposits come from savers, current individual or company accounts, and fixed deposits (Sadalia et al., 2018; Vollmer and Wiese, 2013)). Loans represent granted credits (Y. H. Chung et al., 1997; Shanmugam and Das, 2004). Furthermore,

we have included the LLPs and NPLs as bad outputs. Firstly, non-performing loans are those considered uncollectible according to banking standards. However, the criteria for determining this variable are diverse in the literature, depending on the length of delinquency and the probability of collecting the loans (Barros et al., 2012; Fukuyama and Matousek, 2017; Jiménez-Hernandez et al., 2019; Partovi and Matousek, 2019). Secondly, LLPs are mandatory reserves for possible loan losses (Fukuyama and Matousek, 2017; Park and Weber, 2006). As inputs, operating expenses represent the necessary costs to develop the operation, including fees, services, taxes, depreciation, and amortization (Andrieş and Cocriş, 2010; Matthews, 2013; Sadalia et al., 2018). Finally, personnel costs input is salaries and all social employees' benefits (Cabrera-Suárez and Pérez-Rodríguez, 2021; Řepková, 2015).

Following Paradi et al. (2011) as a methodological point of view, we evaluate the performance of banks using the profitability approach. This method emphasizes how each bank uses its resources (inputs such as operating expenses and personnel costs) to generate revenues such as interest and non-interest incomes, commissions, and the total value of deposits and loans. The analysis reflects the most efficient level of overall costs in generating profits (in US dollar monetary values). It is worth noting that we define LLPs and NPLs (bad loans) according to Ecuadorian banking regulations.[20]

Efficiency environmental factors

We describe a set of variables that could determine efficiency. First, we use a set of factors relative to the study period. Year indicates the moment of each observation used to identify linear time trends. It represents the technological change in efficiency. Other studies have found that this factor improves efficiency as time elapses (Akkaya, 2017). Age variable (bank's experience) is a proxy of its ability (unobserved factor) to remain in the market. It indicates accumulative expertise and knowledge acquired over time (Achi, 2021).

Also, we incorporate a collection of financial indicators. The Gross profit portfolio variable represents a ratio of interest earned to the gross portfolio. This variable is the mean of interest rate over loans. It is interesting because banks need to adjust target profitability into different credit segments based on regulated rates (Meslier et al., 2014). For example, commercial credit tends to be low risk, and the interest rate must be lower than microcredit, which is qualified as

[20] The Monetary and Financial Policy and Regulation Board of Ecuador, in resolution 209-2016, indicates the delinquency terms in which loans should be categorized as uncollectible and represent an expected loss of 100%.

high risk. The Commercial business variable indicates the proportion of commercial loans to total loans. We use it as a proxy for banks' business diversification in credit segments. The higher the ratio, the less diversified the credit segments are. ROA reflects net profitability over total assets. This indicator assesses managerial skills to generate profits with assets (Mutuku et al., 2019; Pointer and Khoi, 2019). Banks with better ROA levels are more attractive to savers and investors, making them more efficient (Stewart et al., 2016).

Finally, Market share reflects the proportion of loans of each bank in the overall market. This factor may be related to the internal policies of each bank (Spulbăr and Niţoi, 2014). For example, if a bank's management intends to expand its market share, it may be at the cost of increased risk in lending. Also, it may be necessary to increase investments; however, such behavior does not guarantee efficiency. The NDTS (non-debt tax shield) variable is the ratio of depreciation to fixed assets (Bukair, 2019). We include this variable as a non-cash expense (DeAngelo and Masulis, 1980) but reduce taxable profits and taxes payable (Wu, 2011). This circumstance allows the taxes saved to increase the funds available for investments (Hanlon and Heitzman, 2010).

We consider other financial indicators related to regulatory standards or Basel III recommendations. The Regulation variable represents a proportion of deposits required by the Central Bank. Benston and Kaufman (1996) argue that governments justify bank regulation through the presence of externalities. For example, events that lead to the possibility of insolvency or bankruptcy of a bank. According to Pessarossi and Weill (2015), Banking system regulators require banks to have sufficient capital to support losses and minimize moral hazard. These circumstances promote financial stability by preventing risk-taking, potential problem loans, or bank failures (Berger and Humphrey, 1997; de Bandt et al., 2021).

The liquidity risk variable is a ratio of loans to total assets. Low levels of this variable can significantly compromise the technical efficiency of banks through additional funding costs, limited investment opportunities, operational risk, loss of customers and reputation, and increased regulatory oversight (Bhattacharya et al., 1998).

As complementary factors, we included a set of dummies. The stock market variable indicates if banks are listed (1) or not (0). It is interesting because listed banks can use the securities market to invest in securities, issue debt, and expand their lending capacity. The ownership variable reflects the composition of the owner's type: individuals and legal entities (1), individuals, legal entities and financial entities (2), foreign individuals and legal entities

(3), and state (4). This variable could be relevant because the ownership composition determines the origin of decisions.

Table 12 shows descriptive statistics for our efficiency models' input and output variables. Also, we have included environmental factors as determinants of efficiency. All value data in $ US are inflation-adjusted in constant 2014 $ US (i.e., we used the consumer price index of Ecuador concerning the base period 2014).

Table 12. Descriptive statistics for 2007-2017 for all banks analyzed (in thousands of $US).

Variable	Mean	Standard deviation	Minimum	Maximum
Good outputs				
Gross Income (net interest income + non-interest (fee) income)	89,122.5	141,137.9	983.7	728,061.2
Deposits total value	1,193,916.7	1,676,366.6	1,483.8	8,344,058.4
Loans total value	831,142.0	1,262,792.5	3,134.2	6,701,174.8
Bad outputs				
Loan loss provisions (LLPs)	14,569.0	29,529.9	0.0	181,214.1
Non-performing loans' total value (NPLs)	3,361.7	6,382.0	0.0	47,571.8
Inputs				
Operational expenses	49,713.5	83,144.6	622.5	428,391.7
Personnel costs	22,699.9	31,344.9	579.1	160,322.0
Environmental factors				
Year	2011.9	3.2	2007	2017
Age	38.5436	24.6045	0	111
Gross profit portfolio	0.1242	0.0392	0.0486	0.4194
Commercial business	0.4593	0.2707	0.0000	1.0000
ROA	0.0078	0.0140	-0.0932	0.0406
Market share	0.0564	0.0821	0.0002	0.3661
NDTS	0.081	0.0465	0.0063	0.2809
Regulation	0.1083	0.0980	0.0000	0.5681
Liquidity risk	0.5279	0.1166	0.0976	0.77
Stock_market	0.6769	0.4689	0	1
Ownership	1.3384	0.8238	1	4

Notes: Descriptive statistics are reported for the pooled sample.

In general, the input and output data reflect a high standard deviation. Two aspects explain this observation: a) the different sizes of banks and b) the growth of banking in financial intermediation transactions during the period studied. Concerning good outputs, the observable difference in the values of deposits and loans is due to regulations that oblige banks to maintain liquidity funds.

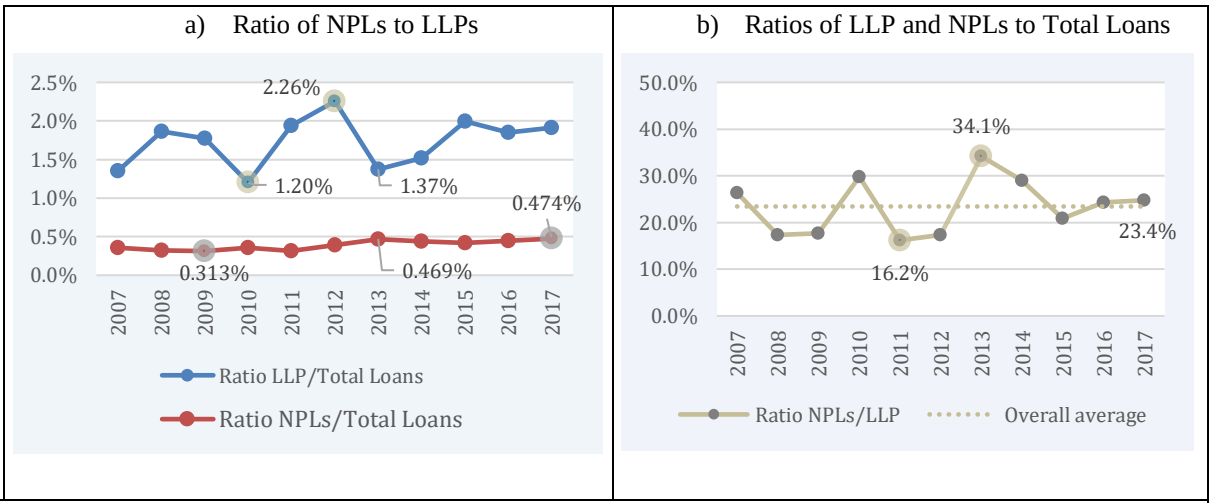
Regarding environmental factors, some financial indicators stand out: gross profit portfolio (12.42%) indicates the average income of the portfolio's composition; commercial business (45.93%) shows that Ecuadorian banks tend to diversify credit segments; ROA (0.78%) is interesting as it seems low, meaning that bank deepening must occur to avoid losses; market share (5.64%) suggests a wide dispersion in the market uptake of loans; NDTS (8.1%) indicates that banks generate cash flow equal to the depreciation rate multiplied by the tax rate.

Other exciting factors are regulation (10.83%) and liquidity risk (52.79%). These factors respond to the control standards to ensure liquidity. The remaining factors are categorical and denote different qualities of each bank.

Focusing on bad outputs, Figure 7a shows the behavior of LLPs and NPLs concerning total loans. The LLPs/total loans ratio shows more significant variability than the NPLs/total loans ratio. The first exhibits a minimum of 1.20% and a maximum of 2.26%, while the second is 0.313% and 0.474%, respectively. The year 2013 stands out, with the lowest difference between the ratios. In interpretative terms, in that year, LLPs were 2.9 times that of NPLs.

Figure 7b shows the relationship between NPLs and LLPs, reflecting the required proportion of LLPs to absorb NPLs. The highest point occurred in 2013, with 34.1%, preceded by two years with ratios below the average. This behavior is similar to what happened between 2008 and 2010. More interestingly, however, is the LLPs coverage of NPLs. The historical average is 23.4%, which means that LLPs cover, on average, 4.3 times the NPLs (100/23.4).

Figure 7. Relationships between NPLs, LLPs, and total loans.



Notes: The LLPs/Total Loans and NPLs/Total Loans ratios are obtained by dividing the annual balances of LLPs and NPLs by Total Loans; the NPLs/LLPs ratio is obtained by dividing the yearly balance of NPLs by the annual balance of LLPs

4.5.2. Estimated efficiencies

Table 13 shows year-by-year efficiency for Models 1 and 2, where LLPs and NPLs are treated as undesirable outputs. The results are organized in three panels indicating the size group: large banks with assets over US$1 billion; medium-sized banks with total assets between US$200 million and US$1 billion; and small banks with assets under US$200 million. All models were estimated using the package "deaR" in R, running year-by-year for all banks.[21] Test results and graphs were obtained with the STATA 14 software package.

In general, we consider two models to evaluate the efficiency of banks in Ecuador. In Model 1, we use operational and labor expenses as inputs. At the same time, we consider the total amount of loans, deposits, and income (interest + fees) as good outputs and LLPs as one undesirable output. On the other hand, Model 2 includes the same inputs and good outputs as Model 1, but loans represent total loans minus NPLs, and NPLs represent an undesirable output.

Regarding Model 1 (also named LLP), in general terms, results indicate that banks are highly efficient, given that the mean efficiency for all years is 92%. Also, there are fully efficient banks yearly because most take efficiency values equal to 1. In average terms, large banks show higher efficiency (94%) than medium and small banks, with small banks being more efficient than medium banks. Finally, the trend of total average efficiency indicates that despite the global financial crisis, efficiency grew since 2009 but decreased in 2016-2017.

In results for Model 2 (also named NPLs), there are exciting differences from Model 1. In general, results indicate that banks are also highly efficient (some fully efficient in the period). However, the rank slightly varies if we consider LLPs or NPLs. It is also worth noting that the group of large banks leads the efficiency ratings with an average of 91%, while the averages for medium and small banks are 87% and 88%, respectively. Also, there are fully efficient banks each year. The mean efficiency for all years is 89%. However, comparing Models 1 and 2, we observe that the trend of efficiencies per year tends to decrease in Model 2 with regards to Model 1 estimates.

The distribution of efficiencies over time and the coefficient of variation for different bank sizes in Model 1 are shown in Figure 8. Regarding the time-varying path of efficiencies (Figure 8a), 2007, 2016, and 2017 show that 50% of the banks denote total efficiency, and the rest dispersed to levels below 0.5. Similar behavior occurred between 2010 and 2013, but with less

[21] Codes used for SBM efficiency were obtained from https://rdrr.io/cran/deaR/man/model_sbmeff.html.

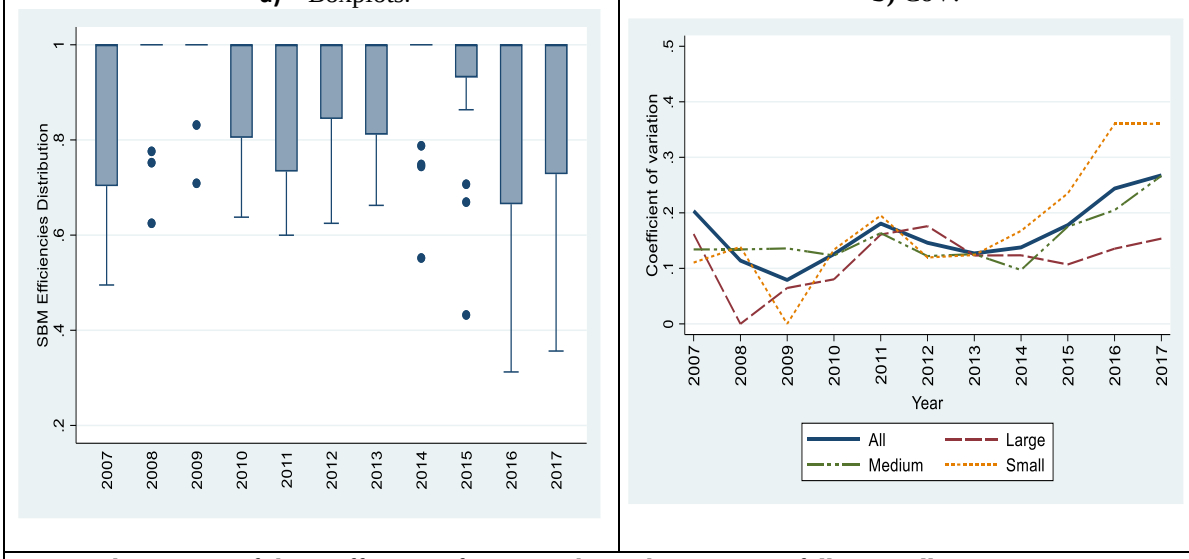
dispersion, with the lowest levels between 0.6 and 0.65. In 2008, 2009, and 2014 most banks obtained efficiencies of 1, and only a smaller group of two or three banks dispersed in levels between 0.85 and 0.5. Finally, in 2015 most banks had to behave close to the maximum level, and some denoted low levels of efficiency. Generally, half of the banks sustained maximum efficiency for a significant time. On the other side (Figure 8b), note that the groups' coefficient of variation (CoV) is closer to the global indicator in 2007 and from 2010 to 2014. In the last part of the period studied, the three groups of banks tended to increase the CoV, more pronounced in small and medium-sized banks and moderately in large banks.

Figure 9 also shows the distribution of efficiencies over time and the coefficient of variation for different bank sizes of Model 2. As we can see, Figure 9a shows that some banks obtained efficiency levels below 0.6, lower than in Model 1. The years 2011 to 2017, except for 2013, show wider dispersion because the interquartile range is more significant. Notably, the years 2009, 2010, and 2013 show high levels of efficiency. The coefficients of variation shown in Figure 9b indicate that large banks tend to be more regular and have a lower coefficient of variation. In contrast, the other groups show more irregularity over time and have higher coefficients of variation. This behavior means that the effective collection management of loans granted is relevant in measuring efficiency.

Table 13. SBM results for Model 1 (LLPs) and 2 (NPLs).

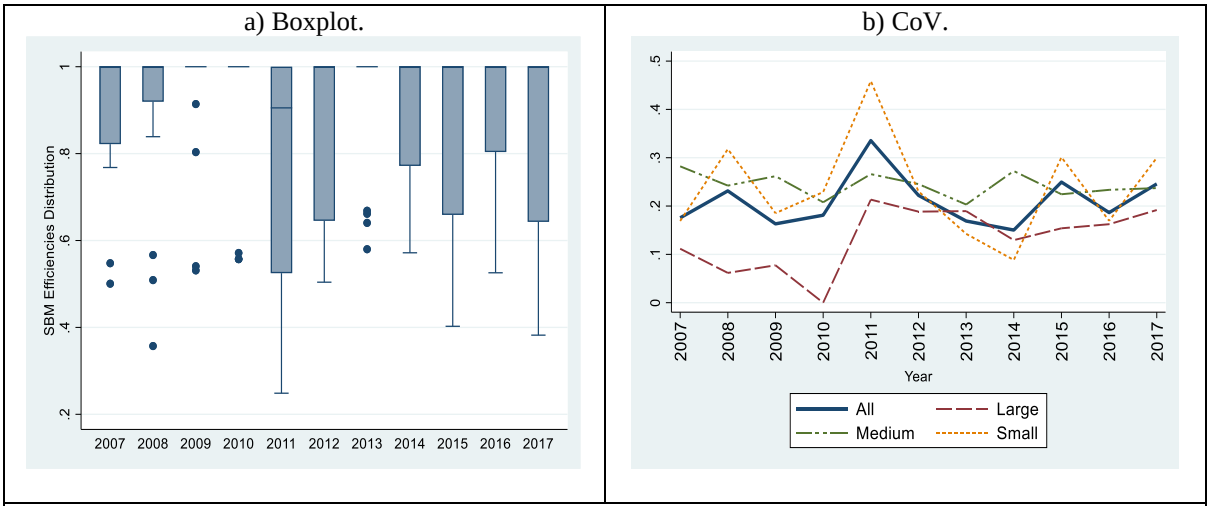
Bank	2007		2008		2009		2010		2011		2012		2013		2014		2015		2016		2017		Mean	Mean	Rank	Rank
	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs	LLPs	NPLs
Panel A: Large banks																										
Austro	1.00		1.00			0.80	1.00	1.00	1.00	1.00	1.00		1.00	1.00	1.00		1.00		1.00	1.00	1.00	1.00	**1.00**	**0.97**	1	3
Pichincha	1.00	1.00	1.00	1.00	1.00		1.00	1.00	1.00	1.00	1.00		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**1.00**	**1.00**	1	1
Internacional	1.00	1.00	1.00		1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.87		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**1.00**	**0.99**	2	2
Pacifico	1.00	1.00	1.00	1.00	1.00	1.00	1.00		1.00	1.00		1.00	1.00		0.74	1.00	1.00		1.00	1.00	1.00	1.00	**0.97**	**1.00**	3	1
Bolivariano	0.75	0.77	1.00	0.84	1.00	0.91	1.00	1.00	1.00	0.68	1.00	0.76	1.00	0.66	1.00	0.75	1.00	0.81	1.00	0.77	0.73	0.67	**0.95**	**0.78**	5	9
Produbanco	0.62	0.82	1.00	1.00	0.83	1.00	0.80	1.00	0.63	0.59	0.71	0.68	0.81	1.00	1.00	1.00	1.00		1.00	1.00	0.89	0.79	**0.84**	**0.89**	8	10
Guayaquil	1.00	0.82	1.00	1.00	1.00	1.00	0.86	1.00	0.74	0.68	0.62	0.60	0.72	0.67	0.75	0.75	0.71	0.66	0.63	0.60	0.65	0.61	**0.79**	**0.76**	10	12
Average	***0.91***	***0.90***	***1.00***	***0.97***	***0.97***	***0.95***	***0.95***	***1.00***	***0.91***	***0.85***	***0.88***	***0.78***	***0.92***	***0.89***	***0.93***	***0.92***	***0.96***	***0.87***	***0.95***	***0.91***	***0.90***	***0.87***	***0.94***	***0.91***		
Panel B: Medium banks																										
Loja		1.00	1.00	1.00	1.00	1.00	1.00	1.00		1.00	1.00	1.00	1.00	1.00	1.00	1.00		1.00	1.00	1.00	1.00	1.00	**1.00**	**1.00**	1	1
Machala	0.63	0.50	0.75	0.51	1.00	0.53	0.78	0.57	1.00	0.52	1.00	0.56	1.00	0.58	1.00	0.57	1.00	0.54	1.00	0.53	1.00	0.57	**0.92**	**0.54**	7	14
Citibank	0.50	1.00	1.00	1.00	1.00	1.00	0.79	1.00	0.70	1.00	1.00	1.00	0.76	1.00	1.00		1.00	1.00	0.63	1.00	0.48	1.00	**0.81**	**1.00**	9	1
Ruminahui	0.69	1.00	0.78	1.00	0.71	1.00	0.74	1.00	0.73	1.00	0.74	1.00	0.80	1.00	0.79	1.00	0.67	1.00	0.70	0.80	0.73	0.71	**0.73**	**0.95**	13	4
Average	***0.61***	***0.88***	***0.88***	***0.88***	***0.93***	***0.88***	***0.83***	***0.89***	***0.81***	***0.88***	***0.93***	***0.89***	***0.89***	***0.90***	***0.95***	***0.86***	***0.89***	***0.89***	***0.83***	***0.83***	***0.80***	***0.76***	***0.87***	***0.87***		
Panel C: Small banks																										
Cofiec	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00		1.00	1.00	1.00	1.00	1.00							**1.00**	**1.00**	1	1
Manabi	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.50	1.00	1.00	1.00	1.00	1.00		1.00		1.00	1.00	1.00	1.00	**1.00**	**0.94**	1	6
Litoral	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.56	1.00	0.36	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**1.00**	**0.90**	1	8
Coopnacional	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.63	1.00	1.00	0.50	1.00	1.00	1.00	1.00	1.00		1.00	1.00	1.00	1.00	**0.97**	**0.95**	4	5
Capital		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.81	1.00	1.00	1.00	1.00	1.00		1.00	1.00		1.00	0.44	0.38	**0.94**	**0.92**	6	7
Delbank	1.00	1.00	1.00	0.36	1.00	1.00	1.00	1.00	1.00	0.25	1.00	1.00	1.00	1.00	0.55	1.00	0.43	0.40	0.31	1.00	0.36	1.00	**0.79**	**0.82**	11	11
Amazonas	0.72	0.55	0.62	0.57	1.00	0.54	0.64	0.56	0.60	0.45	0.70	0.61	0.66	0.64	1.00	0.77	0.86	0.66	0.60	0.58	0.73	0.60	**0.74**	**0.59**	12	13
Average	***0.95***	***0.94***	***0.95***	***0.85***	***1.00***	***0.93***	***0.95***	***0.87***	***0.89***	***0.62***	***0.95***	***0.87***	***0.95***	***0.95***	***0.94***	***0.95***	***0.88***	***0.76***	***0.78***	***0.93***	***0.75***	***0.83***	***0.92***	***0.88***		
Total average	**0.87**	**0.91**	**0.95**	**0.89**	**0.97**	**0.93**	**0.92**	**0.92**	**0.88**	**0.77**	**0.92**	**0.85**	**0.93**	**0.91**	**0.94**	**0.92**	**0.92**	**0.84**	**0.87**	**0.90**	**0.82**	**0.83**	**0.91**	**0.89**		

Figure 8. Time-varying path for boxplot efficiency distributions and coefficient of variation (CoV) in Model 1.



Notes: The average of the coefficients of variation by each group is as follows: All=0.1720, Large=0.1293, Medium=0.1840, Small=0.1961.

Figure 9. Time-varying path for boxplot efficiency distributions and coefficient of variation (CoV) of Model 2.



Notes: The average of the coefficients of variation by each group is as follows: All=0.2158, Large=0.1308, Medium=0.2427, Small=0.2254.

In summary, comparing Model 1 and Model 2 results, we observe that when we included NPLs in the efficiency model as an undesirable output, efficiencies tend to be lower than in other LLPs models. It could indicate that LLPs overestimate the efficiency in the presence of NPLs. This result agrees with many studies that have found that NPLs negatively affect the efficiency and stability of banks because they impair the quality of assets in a bank. Therefore,

we can conclude that NPLs are preferable to LLPs as an undesirable output for Ecuadorian banks because it better captures the effect of uncollectible loans than the provisions for credit losses.

4.5.3. Analysis of the bank's inefficiency

In this section, we study the main causes of inefficiency obtained using input and output slacks in the SBM method.

Following Deng et al. (2020) and Huang et al. (2017), the inefficiency of each input and output was determined as the ratio of input and output slack to its total value. The overall input and output inefficiencies are the averages of the input and output inefficiencies.

Considering that input redundancies and output shortfalls of inefficient banks can be measured based on slacks, we define the inefficiency of *k*-th input as the proportion of input slacks (s_k^-), to the real input $\left(x_{k0}\right)$ and the inefficiency of *q*-th output as the proportion of output slacks $\left(s_q^+\right)$ to the real output $\left(y_{q0}\right)$. The computational formulas are as follows:

$$Inefx_k = s_k^- / x_{k0},\ k = 1,2,3,4,5$$

$$Inefy_q = s_q^+ / y_{q0},\ q = 1,2 \qquad [10]$$

Tables 14 and 15 show the results for input and output inefficiencies defined in equation [10], considering LLPs and NPLs as bad outputs. Also, we have included two years corresponding to the beginning (2007) and the end (2017) of the continuous public administration period, which were taken as a reference to analyze inefficiencies. Next, we briefly explain some interesting results.

Firstly, Table 14 allows us to infer that the LLPs variable has a significant weight in the inefficiency of some banks. For example, the left side shows the results of inefficiencies for 2007. The overall averages are 0.071 and 0.043 for inputs and good outputs, respectively. As we can observe, loan loss provision is the main factor that generates inefficiency in several banks. The inefficiency of this factor ranges between 0.504 and 0.994. Large and medium banks had more inefficiencies than small banks in 2007. On the right side, Table 3 shows the inefficiencies for 2017. As we can see, some large, medium, and small banks have several inefficiencies in all inputs and outputs. It is worth noting that a couple of banks show extraordinary inefficiencies that significantly affect the overall average of goods outputs. However, these same banks do not present bad output inefficiencies.

Secondly, Table 15 shows the results of inefficiencies for 2007 and 2017. While evaluating the influence of LLPs as part of bank regulation is interesting, observing the effect of NPLs (bad output) on efficiency is also motivating. The latter is a residual factor of loan collection management.

Although the averages of input and output inefficiencies are low in general, a more detailed analysis reveals motivating aspects. For example, within the inefficient factors, NPLs are the highest in both years. The average inefficiencies of NPLs were 0.124 and 0.302 in 2007 and 2017, respectively. Also, the input and output inefficiency averages were higher in 2017. Moreover, in 2007 five banks had inefficiencies, and in 2017 they added two more.

From an overview of the two models, a set of banks reflects total efficiency in 2007 and 2017 (this does not imply that inefficiencies could exist in the inter period). In contrast, another group of banks shows inefficiencies at the beginning and end of the period studied (with a couple of exceptions). Regarding bad outputs, since the delay in the collection of the loans has an impact on increasing LLP, we can infer that its inefficiency in some banks stems from higher proportions of these (hence, higher ratios of LLP). On the other hand, we can assume that the longer the delay in loan collection, the more latent bad loans (NPLs) are likely to occur. Finally, the evident total efficiency of some banks leads to the conclusion that bank managers can adapt strategies over banking regulations regarding LLPs and NPLs.

Table 14. Comparison of input and output SBM inefficiencies using LLPs as an undesirable output.

	Year 2007								Year 2017							
	Inputs			Outputs					Inputs			Outputs				
Bank	**Operational expenses**	**Personal expenses**	***Mean for inputs inefficiency***	**Deposits**	**Loans**	**Income**	***Mean good outputs inefficiency***	***LLPs***	**Operational expenses**	**Personal expenses**	***Mean for inputs inefficiency***	**Deposits**	**Loans**	**Income**	***Mean good outputs inefficiency***	***LLPs***
Panel A: Large banks																
Austro	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pichincha	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Internacional	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pacifico	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bolivariano	0.163	0.024	0.093	0	0.065	0	0.022	0.801	0.258	0.148	0.203	0	0.103	0.083	0.062	0.164
Produbanco	0.267	0.251	0.259	0	0.064	0	0.021	0.714	0.143	0.038	0.09	0.018	0	0.023	0.014	0.053
Guayaquil	0	0	0	0	0	0	0	0	0.202	0.25	0.226	0.169	0.095	0	0.088	0.527
Panel B: Medium banks																
Loja	--	--	--	--	--	--	--	--	0	0	0	0	0	0	0	0
Machala	0.205	0.273	0.239	0.137	0.17	0	0.102	0.504	0	0	0	0	0	0	0	0
Citibank	0.055	0.503l	0.279	0	0.529	0.301	0.277	0.994	0.388	0.193	0.291	0	0.306	0.986	0.431	0.573
Ruminahui	0.139	0.08	0.109	0.272	0.368	0	0.213	0.535	0.089	0.067	0.078	0.484	0.493	0	0.326	0.042
Panel C: Small banks																
Cofiec	0	0	0	0	0	0	0	0	--	--	--	--	--	--	--	--
Manabi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Litoral	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Coopnacional	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Capital	--	--	--	--	--	--	--	--	0.061	0	0.03	3.278	1.363	0.274	1.638	0
Delbank	0	0	0	0	0	0	0	0	0.025	0	0.012	3.506	1.764	1.815	2.362	0
Amazonas	0.17	0.149	0.159	0	0.138	0	0.046	0.548	0.272	0.174	0.223	0	0.209	0.042	0.084	0.018
Average	***0.063***	***0.08***	***0.071***	***0.026***	***0.083***	***0.019***	***0.043***	***0.256***	***0.085***	***0.051***	***0.068***	***0.439***	***0.255***	***0.19***	***0.294***	***0.081***

Notes: Mean for inputs and good outputs inefficiencies are calculated by averaging expressions defined by equation [2]. Blank cells reflect NA as a result returned by the R program. Cells with dashes mean that there was no data. Zero results represent no inefficiencies.

Table 15. Comparison of input and output SBM inefficiencies using NPLs as an undesirable output.

	Year 2007								Year 2017							
	Inputs			Outputs					Inputs			Outputs				
Bank	**Operational expenses**	**Personal expenses**	***Mean for inputs inefficiency***	**Deposits**	**Loans**	**Income**	***Mean for good outputs inefficiency***	***NPLs***	**Operational expenses**	**Personal expenses**	***Mean for inputs inefficiency***	**Deposits**	**Loans**	**Income**	***Mean for good outputs inefficiency***	***NPLs***
Panel A: Large banks																
Austro	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pichincha	0	0	0	0	0	0	0	0	--	--	--	--	--	--	--	--
Internacional	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pacifico	--	--	--	--	--	--	--	--	0	0	0	0	0	0	0	0
Bolivariano	0.167	0.029	0.098	0	0.065	0	0.022	0.46	0.259	0.144	0.202	0	0.105	0.083	0.063	0.584
Produbanco	0.011	0.144	0.077	0.265	0.262	0	0.176	0	0.159	0.011	0.085	0	0	0.006	0.002	0.633
Guayaquil	0.122	0.009	0.066	0	0.189	0	0.063	0.262	0.202	0.25	0.226	0.169	0.103	0	0.091	0.807
Panel B: Medium banks																
Loja	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Machala	0.373	0.393	0.383	0.011	0.031	0	0.014	0.645	0.193	0.349	0.271	0.12	0.166	0	0.095	0.891
Citibank	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ruminahui	0	0	0	0	0	0	0	0	0.107	0.029	0.068	0.472	0.496	0	0.323	0.293
Panel C: Small banks																
Cofiec	0	0	0	0	0	0	0	0	--	--	--	--	--	--	--	--
Manabi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Litoral	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Coopnacional	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Capital	0	0	0	0	0	0	0	0	0	0.229	0.115	3.2	1.247	0.19	1.545	0.662
Delbank	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Amazonas	0.351	0.251	0.301	0	0.079	0.177	0.086	0.617	0.178	0.386	0.282	0.033	0.156	0	0.063	0.66
Average	***0.064***	***0.052***	***0.058***	***0.017***	***0.039***	***0.011***	***0.023***	***0.124***	***0.073***	***0.093***	***0.083***	***0.266***	***0.152***	***0.019***	***0.146***	***0.302***

Notes: Mean for inputs and good outputs inefficiencies are calculated by averaging expressions defined by equation [2]. Blank cells reflect NA as a result returned by the R program. Cells with dashes mean that there was no data. Zero results represent no inefficiencies.

4.5.4. Economic and financial factors explaining bank efficiency

In this section, we evaluate the effects of covariates (determinants) on the non-oriented SBM efficiency using the following linear regression model:

$$Efficiency_{it} = \beta' x_{it} + e_{it}, i = 1, 2, ..., N, t = 1, ..., T \quad [11]$$

where $Efficiency_{it}$ is the SBM efficiency scores previously estimated for Models 1 and 2, respectively; x_{it} is a column vector of explanatory variables (including one for the constant term); β' is a row vector of unknown parameters to be estimated; and e_i is an error term with standard deviation equal to σ_e. Parameters β' and σ_e were estimated based on censored Tobit regression using maximum likelihood.

Equation [11] was estimated in this paper using several determinants. Results are shown in Table 16, distinguishing two models for efficiencies. Model 1 uses LLPs as an undesirable output, and Model 2 uses NPLs as an undesirable output.

As we can see, some determinants are significant in both models, but others affect one or the other model. Linear time trend statistically (10%) and positively influences efficiency in Model 1, indicating technical progress. This result shows the same orientation as the one demonstrated by Akkaya (2017) in his research on banking efficiency in Eurozone countries (although this author used the Cobb-Douglas production function). According to Drakos (2002), the linear time trend could proxy other transition processes aspects, such as improvement in regulation and macroeconomic conditions. Contrary to expectations, Age statistically and negatively affects efficiency in both Models, as Stewart et al. (2016) found when applying the Simar and Wilson methodology to banks in Vietnam. It implies that younger banks are more efficient than older banks. Generally, older banks tend to have higher investment cost structures and expenses and therefore face higher production requirements.

The commercial business variable is statistically significant at 5% and negatively affects efficiency only in Model 1. We can explain this result because commercial credit is less risky but generates less income. However, this characteristic does not exempt banks from creating reserves for bad loans (LLPs). Conversely, replacing commercial credit with consumer or

micro-credit would lead to higher revenues but at higher risks (Dell'Ariccia and Marquez, 2004). This scenario would increase the probability of growing bad loans (NPLs). In this case, we infer that Ecuadorian banks tend to moderate NPLs rather than increase revenues. Other studies, such as Meslier et al. (2014) on Philippine banks, and Nguyen (2018) on banks from six Asian countries, analyzed the effect of diversification of income sources (credit incomes and non-credit incomes). Both emphasize the importance of maintaining a balance between profit and risk, regardless of income source.

Table 16. Determinants of efficiency using the Tobit regression.

Variables	**Model 1**	**Model 2**
Linear time trend	**-0.0225***	-0.00605
	(0.0116)	(0.0129)
Age	**-0.00778***	**-0.00987*****
	(0.00413)	(0.00378)
Gross profit portfolio	-0.232	1.914
	(1.611)	(1.824)
Commercial business	**-0.619****	-0.0992
	(0.256)	(0.253)
ROA	**5.686***	**5.749***
	(3.089)	(2.956)
Market share	**3.960*****	**4.539*****
	(1.497)	(1.466)
NDTS	**-3.938*****	-1.941
	(1.189)	(1.324)
Regulation	**1.704*****	1.038
	(0.657)	(0.698)
Liquidity risk	-0.0735	**1.112***
	(0.461)	(0.612)
Stock market	**-0.452****	-0.265
	(0.198)	(0.175)
Ownership	-0.122	**0.524****
	(0.0843)	(0.248)
Constant	47.58**	12.30
	(23.27)	(25.87)
σ_e	0.2508***	0.3133***
	(0.0284)	(0.03614)
Observations	186	177

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Bold numbers indicate that coefficients are statistically significant at the conventional levels.

Concerning ROA is statistically significant at 10% for both models, and the results show a positive relationship with efficiency. The argument supporting this relationship is that the ROA level favors bank users' confidence (Sari and Saraswati, 2017). In contrast, in India, Singh and Thaker (2020)found a negative relationship under bootstrap truncated regression and a positive one when using conventional Tobit regression. Other researchers who found a positive relationship were Goswami et al. (2019) in India and Sari and Saraswati (2017) in Indonesia, using Tobit and OLS methods, respectively. Also, Řepková (2015) found a negative relationship between ROA and efficiency under OLS regression in Czech commercial banks. These contrasts show that ROA is a determinant with an undefined relationship to bank efficiency.

Regarding market share, the result shows a 1% significance and a positive influence on efficiency in the two models. It implies that greater participation in bank deepening, associated with expanding each bank's activities, improves efficiency. Minh et al. (2013) found similar results by applying a Tobit regression to Vietnam's banking sector. However, Spulbăr and Niţoi (2014) found that managerial policies to gain market share in periods of economic growth could result in lower efficiency later on if the economy decreases.

NDTS is statistically significant only for Model 1 at 1% but has a negative impact. Considering that depreciation comes from investments in fixed assets, it makes sense to assume that higher investments are only justified with more operations. Therefore, it is possible to infer that it is necessary to analyze the capacity utilization of fixed assets, for example, measure their turnover (Altman et al., 2017) and the investment growth rate in fixed assets (L. Guo et al., 2020).

Regarding variables related to banking controls, regulation is statistically significant and positively affects efficiency. Kashyap and Stein (1994) argued that reserve requirements could improve bank efficiency by reducing the risk of bank failures and financial crises. They suggested that reserve requirements can help banks have enough liquidity to meet their obligations and withstand unexpected shocks, improving their efficiency. On the other hand, Lee and Chih (2013) and Chortareas et al. (2012) consider that stringent regulation enhances the stability of banks but generates adverse effects on efficiency. In our case, we think that

funds reserve requirements derived from bank regulation generally contribute to the strength of banks. This feature impacts depositor confidence, thereby reducing the inefficiency gap.

Liquidity risk shows a positive and significant level at 10% in Model 2. This result is inverse to that finding by Fernandes et al. (2018) in European banks through Double Bootstrapped Truncated Regression. However, Sarmiento and Galán (2018) found positive effects on foreign banks in Colombia under a stochastic frontier model with random inefficiency parameters. This ambivalence may be due to liquidity levels in each case. For our Ecuadorian case, we consider that the regulation acts in favor of efficiency.

Our results show that the stock market positively impacts efficiency only in Model 1, consistent with Perera et al. (2008) findings in South Asian banks. This effect may be due to the increased reporting requirements and mandatory risk rating in the securities market. In contrast, Sufian (2015) found a negative impact on the Malaysian bank sector through Simar and Wilson's bootstrap OLS regression. Havrylchyk (2006), who found no significant relationship, argues that the Polish stock market does not induce greater discipline in bank management. Finally, the coefficient for ownership is statistically significant at 5% and positive for Model 2. It implies that the type of ownership impacts efficiency levels, as Pessarossi and Weill (2015) findings in Chinese banks. Gross profit portfolio coefficients were not statistically significant at any conventional significance levels.

Chapter 5. Assessing the performance of the Ecuadorian hotel industry under a regulatory period

5.1. Introduction

Ecuador's tourism industry underwent a significant transformation due to government policies implemented in 2007. Some of the main strategies developed by the Strategic Plan for the Development of Sustainable Tourism in Ecuador (PLANDETUR 2020)[22] for 2007-2020 included training and professionalizing tourism service providers, promoting the creation and diversification of innovative tourism products, attracting foreign brands, increasing investment in improving and creating highway and airport infrastructure, and promoting the destination through marketing campaigns to attract different segments of domestic and international travelers. In addition, the plan contemplated updating regulations and laws related to tourism activities, mainly focusing on promoting the adoption of sustainable tourism practices and consumer protection for tourism products and services. These government policies motivated the expansion of hotel supply.

In this scenario, hotel companies faced different challenges which could affect their efficiency. For example, investors expect adequate returns for the line of business, but the Ecuadorian government established general application policies that would impact company management. One was adopting the International Financial Reporting Standard (IFRS) from 2010 onwards. But, undoubtedly, the most significant was the limitation of labor outsourcing, forcing most sectors toward direct and fixed from 2008 onward.

[22] PLANDETUR 2020 was carried out from the Inter-American Development Bank (IDB) Technical Cooperation No. ATN/FG-9903-EC.

In this increasingly competitive market environment, the efficiency of Ecuadorian hotel operations could be crucial for hotel managers and regulators for effective strategic decision-making policies.

The main contribution of this paper is the analysis of determinants of the Ecuadorian hotel industry, an emergent economy in Latin America where the hotel industry has experimented with regulatory reforms and a significant supply increase since 2007 and where studies on this topic are scarce. We focus on analyzing the impact of restructuring and regulatory reforms affecting the efficiency of the hotel sector in Ecuador, such as labor reform and the introduction of IFRS procedures in the analyzed period. We also use other variables related to the financial and economic characteristics of the hotel (e.g., whether high external indebtedness reduced the efficiency, or the market size positively affected the efficiency).

To do this, we have estimated efficiencies in the first step, considering several non-radial, and non-parametric radial models. Using the bootstrap approach, we have also estimated the unknown distribution of the efficiency scores. Then, in the second stage, we analyzed the effect of several determinants on the efficiency of hotels in Ecuador, comparing results from different non-parametric models.

There are two general approaches to estimating efficiency in a non-parametric framework. Most hotel efficiency studies employ radial measures to calculate efficiency using non-parametric methods such as data envelopment analysis (DEA), free-disposal hull (FDH), or robust methods (e.g., order-α and order-*m*). However, there are a few papers that use non-radial methods, such as the slacks-based measure (SBM) method (see the Appendix in Pérez-Rodríguez and Acosta-González (2023) for an overview).[23] In our study, we analyzed determinants by comparing several non-parametric DEA and SBM methods, and bootstrap-DEA and bootstrap-SBM to account for the estimation of the unknown distribution of the efficiency scores. The motivation to use non-radial approaches is twofold.

[23] The non-radial DEA was first proposed by Färe and Knox Lovell (1978), and then was adapted by Pastor et al. (1999). Tone (2001) developed a new non-radial model called the Slacks-Based Measure (SBM).

First, hotel managers could be interested in assessing the inefficiencies of inputs and outputs, and they could also be interested in allowing for the contraction of inputs and expansion of outputs simultaneously (non-oriented models) –although this may not adequately capture a realistic view of the hotels' production processes–. In both scenarios, non-radial approaches to calculate efficiency could be suitable for these issues. The assumption for radial models such as DEA is that there is a proportional change of inputs or outputs, and they usually disregard the slacks in the efficiency scores. The non-radial DEA model, known as the SBM, also enables us to identify the efficiency of the hotel industry. The SBM model works directly with excess inputs and production deficits, accounted for in the efficiency measure. It allows the introduction of a different technology orientation than the classic input- or output-oriented technologies in hotels, such as the non-oriented technology, which allows simultaneous expansion in outputs and contraction in inputs. For example, Deng et al. (2020) applied the super-efficiency SBM model to evaluate the operational efficiency of hotels in China, analyzing inefficiencies in inputs and outputs.

Second, hotel managers could also be interested in applying efficiency assessment methods to avoid the uncertainty of the efficiency score calculation. Hence, it could help better identify and assess the overall operating efficiency of hotels and explore the reasons for inefficiencies, which can help identify optimal resource allocation for improving the competitiveness of hotels. For example, the non-parametric nature of DEA makes hypothesis testing difficult; however, bootstrapping alleviates this weakness (Simar and Wilson, 1998). Bootstrap efficiency is a more robust and effective approach involving estimating the unknown distribution of the efficiency scores (Simar and Wilson, 1998, 2000). Therefore, it could estimate the true distribution of the efficiency scores by performing statistical tests or conducting further analyses and avoiding uncertainty in small samples. Some papers using bootstrap-DEA scores in hotel efficiency are Assaf and Cvelbar (2010), Assaf et al. (2010), and Assaf and Agbola (2011), among others (see literature review in Ablanedo-Rosas et al. (2023)). However, bootstrap SBM has not yet been used in hotel efficiency analysis, although it has been used by Wang et al. (2020) for China's iron and steel industry.

The sample data corresponds to 93 Ecuadorian hotels from 2007 to 2017, when Ecuador's regulatory reforms were more intense.

The rest of this paper is structured as follows: Section 5.2 briefly outlines the Ecuadorian hotel industry. Section 5.3 describes empirical literature on this field. Section 5.44 describes radial (DEA and bootstrap-DEA) and non-radial (SBM and bootstrap-SBM) models. Section 5.5 presents the data used and the empirical results. Finally, the main conclusions drawn are presented in Section 5.6.

5.2. Ecuadorian's hotel industry

At the beginning of this century, the Ecuadorian hotel sector faced different challenges and opportunities from the economic, social, and political environment. For example, the 1999 financial crisis led the government to implement extraordinary measures to control inflation and other macroeconomic factors in the following years. With the beginning of the public administration in 2007 and the set of reforms that accompanied it, expectations for the hotel sector were uncertain. However, the boost to the economy in subsequent years augured well for the development of the sector.

Figure 10a shows the behavior of Ecuador's GDP, tourism GDP, and lodging GDP in the period 2007-2017. As we can see, the GDP grew 39.1% from 2007 to 201724 (Central Bank of Ecuador, 2018). The share of tourism in GDP was not affected by the post-2014 economic slowdown. However, the accommodation sector remained mostly stable during this period. Tourism activity contribution to GDP ranges between 1.87% and 2.1%, including the contribution of the lodging sector, which was between 0.38% and 0.4% (Ministry of Tourism, 2018).

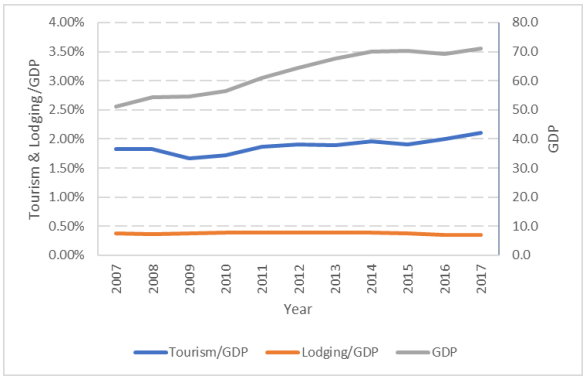
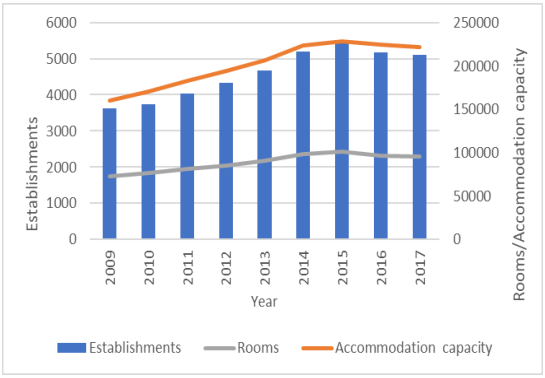
On the other hand, Figure 10b shows the behavior of the lodging offer in the period 2009-2017 (Ministry of Tourism, 2018). It exhibits continued growth through 2015 and a decreasing pattern after 2016.25 It includes any category registered and controlled by the Ministry of Tourism: hotels, hostels, apartment hotels, inns, bungalows, guest houses, motels, and other lodgings.

[24] Calculated at constant prices of 2007.

[25] Data for 2017 are estimates due to missing data in accommodation classifications other than hotels. For this we take into account the lodging contribution to GDP of 2017.

Ease of access to and egress from lodging establishments investments other than hotels and hostels promote the rapid adaptation of supply for small businesses, such as inns, guest houses, or bungalows. Hotels, on the other hand, generally tend to face more significant challenges in entering and exiting the market due to the size of the investment in infrastructure and equipment. Overall, the number of hotels increased significantly from 560 in 2009 to 820 in 2015, representing an increase of 46.4%. Then, in 2017, the number of hotels grew to 880, equivalent to a rise of 7.3%.26 Therefore, we can infer that the reduction in supply comes from other lodging classifications.

Figure 10. Trends of lodging offer and its contribution to GDP.

a) Tourism and lodging contribution to GDP	**b)** Evolution of lodging offer
	

Notes: Figure 10a: GDP represents the gross annual product in billions (constant values); Tourism/GDP and Lodging/GDP represent the percentage contribution to GDP. Figure 10b: The rooms and the accommodation capacity correspond to the lodging establishments; all indicators represent units.

During the studied period (2007-2017), specific regulations that affect business management and performance were implemented. Between 2010 and 2012, the government made applying IFRS mandatory, which may have impacted the hotel industry significantly (Koufodontis et al., 2021). One fundamental change under IFRS is the requirement for hotels and other companies to recognize fixed assets at their fair value (Tawiah and Boolaky, 2020),

[26] Disaggregated data available in tourism statistics bulletins 2009-2013 and 2013-2017 published by the Ministry of Tourism of Ecuador.

leading to periodic revaluation to align with market fluctuations. Additionally, IFRS mandates hotels to calculate depreciation expenses based on estimated useful lives, potentially differing from previous accounting standards. These depreciation methods and asset revaluation changes can substantially impact a hotel's financial statements. For example, variations in the economic value of assets would represent a larger or smaller input value, affecting efficiency. Also, asset revaluations are adjusted in stockholders' equity, impacting the financial indicators of equity profitability and capital structure (Awaliyah et al., 2021).

Another important public policy for its effect on business performance was the 2008 labor reform. It established the abolition and prohibition of outsourcing, labor intermediation, contracting by the hour, and any practice to make labor relations more precarious. This policy had a direct impact both on the hiring of employees and on the conditions of those who offered their labor. It gave rise to temporary hiring for months, which could be converted into indefinite hiring under certain circumstances. For example, after a trial period, the employer must decide whether to terminate the employment relationship or continue with an unlimited contract. The disadvantage of temporary hiring is that the employer would already have incurred recruitment and training costs (Denvir and McMahon, 1992). In addition, this temporary hiring leads to staff turnover, which hurts the quality of service (Johnson, 1981). While fixed labor contracts offer advantages like staff stability and improved service quality to maintain market share (Knox and Nickson, 2007), they pose challenges. For example, fixed contracts limit flexibility to adjust the number of employees to seasonal demand changes, meaning that cutting labor costs with many fixed-contract employees during low-demand periods is complex. Therefore, hotels must assess their unique needs when deciding on hiring strategies.

5.3. Literature review

Most of the papers analyzing hotel efficiency have used a non-parametric approach. This approach can be further distinguished as deterministic (robust and non-robust) or stochastic.

On the one hand, in the deterministic case, the approach most commonly taken is that of data envelopment analysis (DEA). This approach is based on linear programming techniques, does not impose any assumptions regarding functional form, and does not take random error into account. To our knowledge, Morey and Dittman (1995) were the first to use it to measure the performance of the USA hotel industry (in a comparison of 54 hotels) using DEA, providing a helpful reference in the selection of input and output variables. Several authors have also made valuable contributions by analyzing hotel technical efficiency in several territories. For example, Anderson et al. (2000), Brown and Ragsdale (2002) and Reynolds and Thompson (2007) for the USA; Hwang and Chang (2003) and Chiang et al. (2004) for Taiwan; Barros (2005) and Barros et al. (2011) for Portugal; Botti et al. (2009) for France; Fernández and Becerra (2013), Parte-Esteban and Alberca-Oliver (2015), Cordero and Tzeremes (2018) for Spain; and Higuerey et al. (2020) for Ecuador; among many others. It is also noteworthy that DEA has been used to estimate cost efficiencies (Spulbăr and Niţoi, 2014; Wang et al., 2006).

Some papers cited above have used bootstrap-DEA, such as Barros et al. (2011), Parte-Esteban and Alberca-Oliver (2015), or other studies such as Barros and Dieke (2008), Assaf et al. (2010), Assaf and Cvelbar (2010), Assaf and Agbola (2011), Oukil et al. (2016), or Tan and Despotis (2021), among others.

All the papers cited above have applied the radial DEA model to assess the hotel efficiencies, assuming that inputs or outputs changed with their proportions and ignoring the slacks that exist in efficiency. However, it is noteworthy that the non-radial DEA model, known as the slacks-based measure (SBM), has also been used. This approach allows us to assume that inputs and outputs are both controllable. Some papers that identify the efficiency of the hotels using the SBM model are Sun and Lu (2005), which assess the performance of 55 Taiwanese hotels in 2001 regarding managerial, occupancy, and catering efficiencies. The SBM model of super-efficiency is also used by Ashrafi et al. (2013) for Singapore and Deng et al. (2020) for mainland China, among others. For example, Deng et al. (2020) evaluated the efficiency of hotels in 31 provinces and four regions in mainland China (Eastern, Western, Central, and North-eastern China). They found that hotels had operational inefficiencies but relatively greater efficiency in Eastern China than other regions.

Unlike the above papers, another deterministic approach allows us to model the dynamic changes in efficiency. The productivity change has been studied using several estimators such as the DEA-Malmquist (e.g., Hwang and Chang (2003) for Taiwan; Barros and Alves (2004), Barros (2005b) for Portugal; De Jorge and Suárez (2014) and Cordero and Tzeremes (2017) for Spain, and Barros and Dieke (2008) for African hotels). Also, Cruz (2017) used SBM-Malmquist in the Philippines hotel sector. But also the non-convex frontiers (which relax the convexity assumption in DEA) based on robust order-m estimators such as Tzeremes (2019, 2021). This author used the Luenberger and Malmquist indices to evaluate the Balearic and Canary Islands hotels' productivity levels during the economic crisis.

On the other hand, literature has produced non-parametric stochastic frontier methods by introducing flexibility into modeling technologies. That is because DEA cannot consider statistical noise, and efficiency estimates may be biased if stochastic elements largely characterize the production process. For example, Shang et al. (2010) were among the first to apply stochastic DEA (SDEA), previously developed by Land et al. (1993), to evaluate hotel efficiency in Taiwan.

Although Higuerey et al. (2020) have studied Ecuadorian hotel efficiency using DEA, to our knowledge, studies have yet to analyze the hotel sector in Ecuador comparing DEA and SBM methods.

5.4. DEA and SBM models

In this study, DEA, a non-parametric mathematical programming approach for frontier estimation, is employed for both radial and non-radial approaches.

5.4.1. Notation

Let n be observations of hotels (or, in general, decision-making units (DMUs)) $j = 1, 2, ..., n$. Let x_{ij} be the observed level of the i-th input at DMU j and let $x = \left(x_{1j}, ..., x_{kj} \right) \in \Re_+^k$ be the vector of k inputs for the i-th unit; y_{rj} is the observed level of the

r-th output at DMU *j*, where $y=\left(y_{1j},...,y_{mj}\right)\in\Re_{+}^{m}$ is a vector of *m* outputs. Technology is defined as $T=\left\{\left(x,y\right):x\ can\ produce\ y\right\}$, and the input requirements and output sets are defined as $L\left(y\right)=\left\{x:\left(x,y\right)\in T\right\}$, $y\in\Re_{+}^{m}$ and $P\left(x\right)=\left\{y:\left(x,y\right)\in T\right\}$, $x\in\Re_{+}^{k}$, respectively. Let ϕ be the radial efficiency score (value between 0 and 1) and ρ^{*} the non-radial efficiency score (which also allows values greater than one); λ_j the optimal weights of the referenced units for unit *j*; s_i^- the input slack/excess for the *i*-th input, and s_r^+ the output slack/shortfall for the *r*-th output.

5.4.2. Basic DEA models

The basic models of DEA are CCR and BCC, proposed by Charnes et al. (1978) and Banker et al. (1984), respectively. CCR involves technology with constant returns to scale (CRS), while BCC enables the inclusion of variable returns to scale (VRS).

Considering the input-oriented models (because the amount of business available to a branch depends mainly on customer demand for the hotel's services and is beyond the branch manager's control), we specify a BCC model which can be written as follows:

$$\begin{aligned}&\min_{\phi,\lambda}\ \phi\\&subject\ to:\\&\qquad y_{r0}=\sum_{j=1}^{n}y_{rj}\lambda_j\\&\qquad \phi x_{i0}-\sum_{j=1}^{n}x_{ij}\lambda_j=0\\&\qquad \sum_{j=1}^{n}\lambda_j=1\\&\qquad \lambda_j\geq 0,\ \forall j\end{aligned}\qquad [12]$$

where sub-index 0 represents the DMU being evaluated in the set of $j = 1, 2, ..., n$ DMUs and incorporates the convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$. For this model ϕ represents "pure" technical efficiency (PTE) (without any consideration of scale).

5.4.3. SBM models

Tone (2001) recommended using the SBM model based on slacks to evaluate the relative efficiency of DMUs. The SBM model based on VRS technology can be written as follows:

$$\rho^* = \min_{\rho,\lambda} \rho = \frac{1 - \frac{1}{k}\sum_{i=1}^{k} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{m}\sum_{r=1}^{m} \frac{s_r^+}{y_{r0}}}$$

subject to:

$$y_{r0} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \qquad [13]$$

$$x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^-$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j, s_i^-, s_r^+ \geq 0, \forall j, i, r$$

The optimal ρ^* is the efficiency of the SBM model: $0 \leq \rho^* \leq 1$ when $\rho^* = 1$ the DMU is fully efficient, because $s_i^- = s_i^+ = 0$, and when $0 \leq \rho^* < 1$ the DMU is inefficient.

5.4.4. Bootstrap-DEA and SBM

Following the procedure of Simar and Wilson (1998), bootstrap-DEA and SBM can be applied in the following steps such as (Wang et al., 2020):

1) Compute $\hat{\phi}_j, j = 1, ..., n$, for example, by the linear programs [11] and [13], respectively.

2) Use the smooth bootstrap to generate a random sample of size *n* from $\hat{\phi}_j$, providing $\tilde{\phi}_{1b},...,\tilde{\phi}_{nb}$, with *b* being the *b*-th replica. Simar and Wilson (1998; Section 4, page 56) explain this procedure in more detail.
3) Compute the estimated bootstrap input as $\tilde{x}_{jb} = \frac{\hat{\phi}_j}{\tilde{\phi}_{jb}} x_j$, $j = 1,...,n$.
4) Compute the bootstrap efficiency estimate $\hat{\phi}_{jb}$ of $\hat{\phi}_j$ by solving equations [11] and [13] for each *b*.
5) Repeat steps 2-4, *b*=1,…, *B* times to provide $\hat{\phi}_{jb}$.

5.5. Empirical results

5.5.1. Data

We used unbalanced panel data from the Superintendency of Companies, Securities, and Insurance (SUPERCIAS) to estimate the efficiencies from 2007 to 2017. We discriminated against those companies that did not report financial information or sales for at least four continuous years within the period studied. Therefore, we obtained a sample of 93 hotels scattered throughout the country's regions. We selected a set of indicators (inputs and output) to analyze efficiency under DEA methodologies and other potential determinants of efficiency (environmental factors), whose incidence is measured through regressions, such as the Simar and Wilson, and Tobit procedures.

Inputs and outputs

As in Barros (2005a), and depending on the data availability, inputs are measured by (i) the number of full-time equivalent workers and labor expenses (cost of salaries plus employee benefits), (ii) material expenses (includes amenity costs), and (iii) other expenses. Output is determined by total revenue. All value data in $US are inflation-adjusted in constant 2014 $US (i.e., we used the consumer price index of Ecuador concerning the base period 2014).

Efficiency environmental factors

To establish determinant factors of efficiency, we select a set of variables representing several aspects: regulatory characteristics, hotel characteristics (financial and economic), and control variables.

Regarding regulatory characteristics, we include two variables related to public policy. The IFRS variable distinguishes the periods when hotel companies adopted the international financial reporting standards that replaced the Ecuadorian accounting standards. This change occurred between 2010-2012. Banker et al. (2014) argued that IFRS contributes to improved productivity for adopters through the quality of financial reporting standards. The other variable is labor reform, which recognizes the change in labor law regulating the hiring type as of 2008.

Regarding hotels' financial and economic characteristics, we distinguish the following variables: the operative return, calculated by dividing operating gains by total assets, reflects management's ability to generate operating profits based on available assets (Aissa and Goaied, 2016; Kim et al., 2012) and manage cost and expense structure (W. H. Greene and Segal, 2004). According to Stewart et al. (2016), better operating returns lead to lower-cost financing opportunities, improving efficiency.

As another economic variable, we include the market share, which indicates the percentage of revenue each hotel obtains from the total market. It is obtained by dividing each hotel's annual income by the sample's total income. This factor is conditioned by the room rates and the accommodation capacity of each hotel, reflecting the sales objectives reached by the hotel (De Jorge and Suárez, 2014). We also include the debt leverage variable representing the level of assets financed with external resources.[27] It is determined by dividing total liabilities by total assets. Debt leverage allows hotels to access additional capital for different purposes, such as expanding, renovating, or acquiring new properties. Its importance lies in management's ability to obtain favorable financing for the company's profit objectives (e.g., improving yields but avoiding excessive financial risk (Skalpe, 2003)).

[27] Hotel managers must consider two important aspects: expected profits, and the cost of debt. The growth of competition may condition revenues and the perceived risk of these revenues may raise the cost of debt. Therefore, debt financing may be critical for companies with limited financial flexibility to adjust debt levels if necessary (Gamba and Triantis, 2008).

We have included the age variable representing the experience (Assaf and Cvelbar, 2010), brand reputation (Wang et al., 2006), and increased management skills (Achi, 2021) to remain in the market. We also included some dummy variables related to size, being listed or not on the stock market, source of capital, global financial crisis, and others related to government regulations such as labor reform and IFRS. Hence, large assets identify hotels whose size, based on their assets, is in the sample's top quartile. This variable is generally associated with economies of scale that facilitate retaining profits to expand operations (Assaf et al., 2010). The listed variable differentiates those hotels listed on the stock market, assuming they manage their finances better (Honma and Hu, 2012). The foreign capital variable identifies hotels with foreign capital and which could adopt global management strategies (G. E. Halkos and Tzeremes, 2007; Oukil et al., 2016). Finally, following Cordero and Tzeremes (2018), we use a crisis period variable to recognize those hotels operating during the financial crisis years. The labor reform variable identifies the transition period when new labor rules were implemented. Finally, the IFRS variable specifies the transition years from Ecuadorian accounting standards to international standards.

Finally, we include some control variables as multiple categorical variables. A couple of these can indicate how they compete in the marketplace: category represents the qualification status (star ranking from 0 to 5) of each hotel (Assaf and Cvelbar, 2010); and legal structure to classify the associative figure—stock corporation (1), limited liability company (2), and company with government participation (3). Finally, the region — (Costa (1), Sierra (2), Amazonia (3), Galapagos (4)— and province variables represent each hotel's geographic location. These factors are relevant because different economic and social contexts as well as specific tourist attractions could influence commercial business strategies (Deng et al., 2020; Higuerey et al., 2020; C. W. Huang et al., 2017).

Table 17 shows the descriptive statistics for the inputs and output used in the efficiency models and the environmental factors used as estimated efficiency determinants. We can emphasize some statistics; for example, the number of employees stands out by the minimum (1) corresponding to four DMUs in initial or final operating periods. The labor costs are more significant than material costs in average terms. However, other expenses represent the largest operational burden, reflecting the level at which the lodging sector needs operating

leverage to generate revenue. The mean of hotels' total revenue is around 2.8 million dollars, greater than the average expenses.

Regarding environmental factors, we can say the following: the operative return mean is 0.075 (7.5%), reflecting lodging industry management skills to obtain returns on assets even though there are observations with negative returns; the market share mean represents 1.3%, indicating that the market is widely distributed; and the debt leverage mean indicates 49.1%, showing that the hotel sector is partially using external funds to finance its assets. Age shows that the average lifetime is 21 years. The percentage of large assets indicates that 25.1% are classed as large hotels; hotels listed in the Ecuadorian security market represent 4.5%, which is low; and 26.7% of hotels have foreign investment.

Table 17. Descriptive statistics of inputs, outputs, and environmental factors from 2007-2017.

Variables	Mean	Sd	Min	Max
Inputs				
Full-time employees	78.7	106.0	1	777
Labor expenses ($)	786,857	1,110,791	2,981	6,666,307
Material expenses ($)	439,411	719,854	143	4,336,408
Other expenses ($)	1,203,311	1,787,509	2,256	12,063,383
Output				
Total revenue ($)	2,830,484	4,294,040	9,594	29,226,821
Environmental factors				
Operative return	.075	.110	-.757	.653
Market share	.013	.021	3.97e-05	.153
Debt leverage	.491	.278	.003	1.386
Age	21.355	13.547	1.3	69.3
Large assets	.251	-	0	1
Listed	.045	-	0	1
Foreign capital	.267	-	0	1
IFRS adoption (2010-2012)	0.201	-	0	1
Labor reform (2008-2009)	0.142	-	0	1
Crisis period (2007-2008)	.121	-	0	1
Category	3.579	-	0	5
Legal structure	1.267	-	1	3
Region	1.689	-	1	4
Province	7.08	-	1	13

Notes: Descriptive statistics are reported for the pooled sample.

Concerning control variables used as fixed effects, the average category indicates most hotels are between three and four stars (3.6), while the predominant legal structure is a stock corporation (1.2). Most lodging establishments are in the Costa and Sierra regions (1.7) (the most popular regions for domestic tourism) and, to a lesser extent, in the Amazonia and Galapagos regions (the most popular regions for international tourism). Finally, the data sample includes hotels from 13 provinces (Ecuador has 24 provinces). According to the sample, Guayas, Pichincha, and Azuay have the most significant number of hotels.

5.5.2. Estimation results

DEA, bootstrap-DEA, and SBM models were estimated using the package "deaR" written in R by Coll-Serrano et al. (2022). Bootstrap-SBM was specifically programmed in R by a colleague (see acknowledgments). Test results were obtained with the STATA 15 software package.

5.5.2.1. Comparing overall efficiency method results

Table 18 shows year-by-year average efficiencies for DEA under basic BCC and bootstrap BCC models ($\hat{\bar{\phi}}^{BCC}$ and $\hat{\bar{\phi}}^{BCC,b}$, respectively) and for the SBM and bootstrap SBM models ($\hat{\bar{\rho}}^{*,SBM}$ and $\hat{\bar{\rho}}^{*SBM,b}$). The number of replicas for the bootstrap-DEA and SBM estimations is 2000.

The main results are varied. First, average hotel efficiency in Ecuador is high but not entirely efficient, considering all non-parametric methods and years (e.g., the efficiency range varies between 0.65 and 0.78). It indicates that the Ecuadorian hotel industry needs to improve the use of its production resources. Second, comparing the average bootstrap-SBM efficiencies with the other models, we observe that they are lower than the rest. Furthermore, it is noteworthy that the interquartile range of bootstrap-SBM is lower than the bootstrap-DEA results over time (see Figure 11). It indicates that the dispersion of the true distribution under bootstrap-DEA is slightly larger than the bootstrap-SBM.

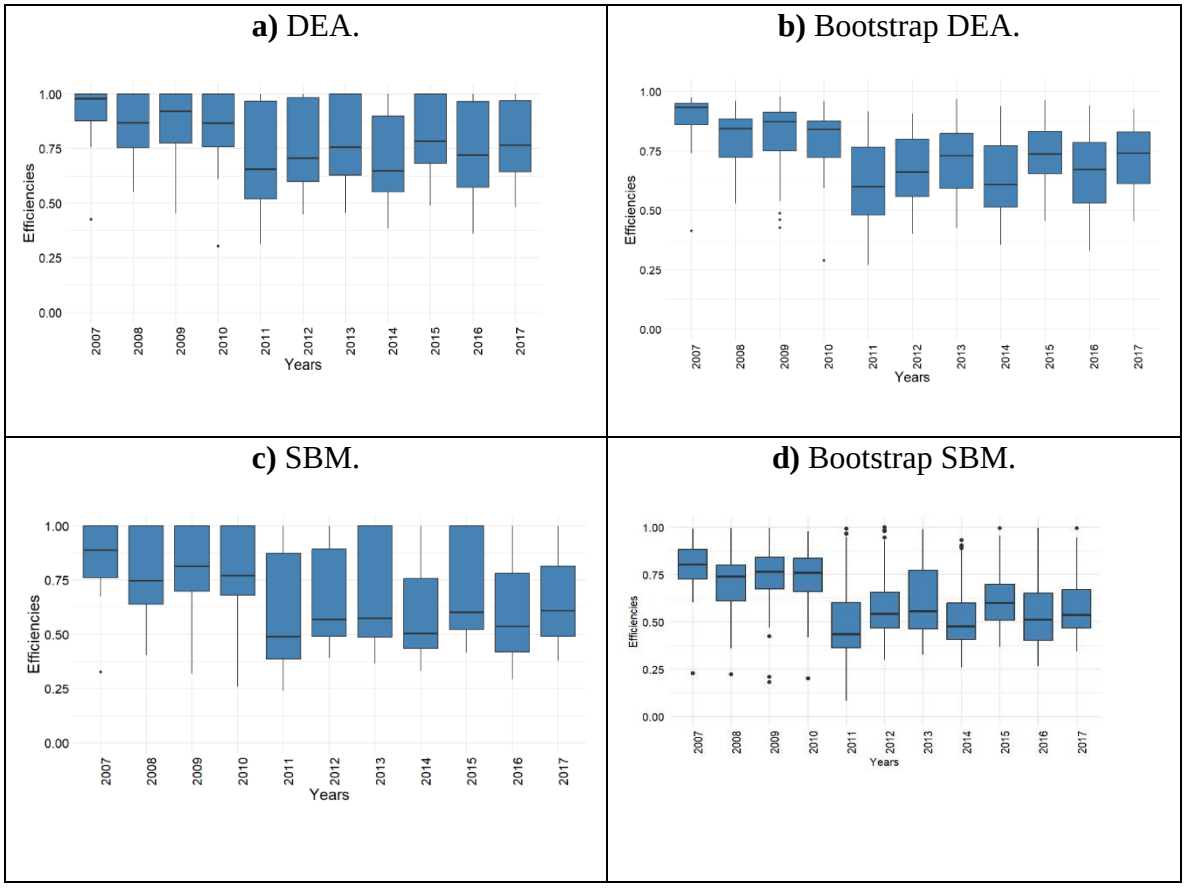
Table 18. Mean efficiency results for DEA and SBM models.

Year	*n*	*DEA*				*SBM*				*Kruskal-Wallis (KW) test*			
			Bootstrap				*Bootstrap*						
		$\hat{\hat{\phi}}^{BCC}$	$\hat{\hat{\phi}}^{BCC,b}$	*Confidence interval*		$\hat{\hat{\rho}}^{*,SBM}$	$\hat{\hat{\rho}}^{*SBM,b}$	*Confidence interval*		*DEA and SBM*	*Bootstrap DEA and SBM*	*DEA and Bootstrap SBM*	*Bootstrap DEA and bootstrap SBM*
				$2.5\%_{low}$	$97.5\%_{up}$			$2.5\%_{low}$	$97.5\%_{up}$				
2007	46	0.930	0.895	0.822	0.929	0.870	0.844	0.588	0.999	0.0970	0.7078	0.0038	0.0567
2008	54	0.858	0.799	0.712	0.857	0.783	0.750	0.456	1.000	0.0427	0.7540	0.0027	0.0959
2009	63	0.867	0.817	0.731	0.866	0.813	0.775	0.437	0.997	0.1861	0.6067	0.0033	0.1439
2010	71	0.853	0.798	0.722	0.852	0.793	0.750	0.529	1.000	0.0234	0.6492	0.0001	0.0222
2011	80	0.699	0.616	0.528	0.697	0.589	0.535	0.288	1.000	0.0006	0.0760	0.0001	0.0006
2012	88	0.751	0.678	0.603	0.749	0.657	0.603	0.451	1.000	0.0001	0.0341	0.0001	0.0001
2013	89	0.776	0.712	0.636	0.775	0.678	0.652	0.406	0.996	0.0008	0.0858	0.0001	0.0062
2014	92	0.705	0.630	0.555	0.704	0.607	0.552	0.395	0.994	0.0001	0.0149	0.0001	0.0001
2015	89	0.798	0.735	0.666	0.797	0.689	0.665	0.445	0.992	0.0001	0.0059	0.0001	0.0002
2016	81	0.725	0.648	0.566	0.724	0.615	0.561	0.348	1.000	0.0006	0.0558	0.0001	0.0006
2017	71	0.794	0.728	0.651	0.793	0.666	0.610	0.458	0.995	0.0001	0.0050	0.0001	0.0001
Averaged	*75*	*0.784*	*0.719*	*0.641*	*0.783*	*0.691*	*0.648*	0.427	0.997	0.0001	0.0021	0.0001	0.0001

Notes: *n* represents the hotel's number each year. The column under the symbol $\hat{\hat{\phi}}^{BCC}$ shows the results for the basic DEA model, and the bootstrap columns show the results for bootstrap DEA $\hat{\hat{\phi}}^{BCC,b}$. The column under the symbol $\hat{\rho}^{*SBM}$ shows the results for the SBM model, and the Bootstrap columns show results for the Bootstrap SBM $\hat{\rho}^{*SBM,b}$. Kruskal-Wallis (KW) indicates the p-values for the test applied to evaluate differences between DEA and SBM models.

Third, statistical differences exist between DEA and SBM efficiencies using the Kruskal-Wallis (KW) test at a 5% significance level. These differences become more significant for DEA ($\hat{\bar{\phi}}^{BCC}$) and bootstrap-SBM ($\hat{\rho}^{*SBM,b}$) models because the null hypothesis is rejected for all years. However, these differences do not allow us to choose the better model.

Figure 11. Time-varying path for boxplot distributions of efficiencies.



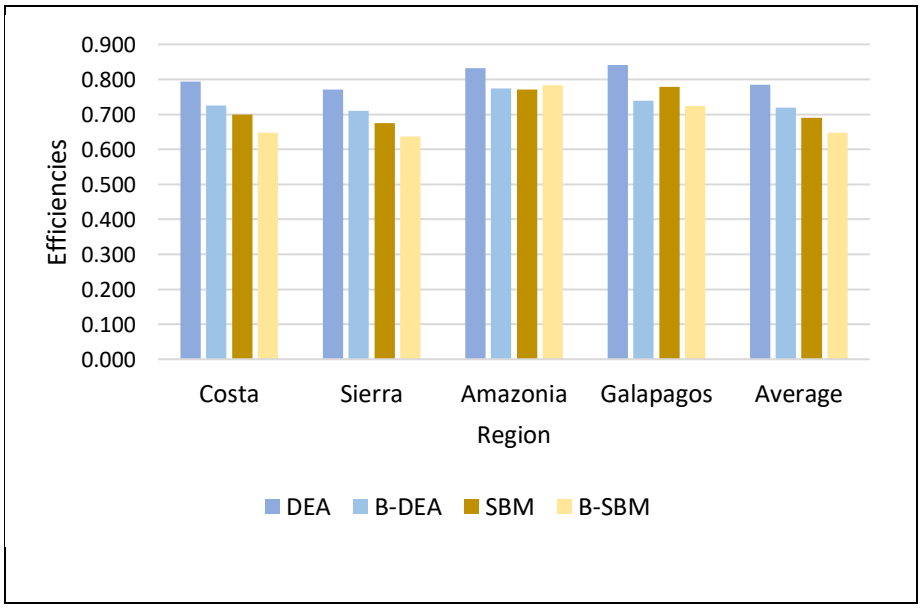
Fourth, there is a decreasing trend of hotel efficiencies over time for all methods. Figure 11 depicts the boxplots for these efficiencies. In general, median efficiencies decreased from 2007 to 2017 for all methods. Also, we observe two differentiated periods: from 2007 to 2010 and 2011 to 2017. These two regimes could be related to two legal aspects. First, the global financial and economic crisis of 2007 and the government decree which eliminated labor outsourcing in 2008. As a result, companies were obliged to hire with higher fixed costs and

expenses. Second, IFRS were implemented in 2010-2011 (for large companies) and 2011-2012 (for small and medium-sized companies). This process implied a transitory adjustment, which could provoke a change in efficiencies between 2010 and 2012.

5.5.2.2. Efficiencies by region

Figure 12 shows the average regional efficiencies by non-parametric models (see Appendix, Table A2 for estimation results). In general, all regions have lower non-radial average efficiencies than radial ones. This exciting result could imply that radial models can overestimate efficiencies regarding non-radial methods.

Figure 12. Mean efficiency by region and non-parametric estimators.



Next, we analyze the coefficient of variation (CoV), which reflects the dispersion effect of the efficiencies (see Appendix, Table A3 for estimation results). Figure 13 shows the time path of these coefficients for the overall sample and the four Ecuadorian regions. The main result is that the CoV increased over time in all cases, although we can see that the SBM and bootstrap-SBM procedures increased CoV more than with DEA and bootstrap DEA.

Figure 13. Time-path dynamics of the coefficient of variation (CoV) per region.

***Notes*:** The averaged CoV of each model is DEA = 0.236; Bootstrap DEA 0.216; SBM = 0.330; Bootstrap SBM = 0.338.

5.5.2.3. The hotel's inefficiency analysis

In this section, we analyze the inefficiencies produced by inputs and outputs on a slack basis using the DEA and SBM methods (T. H. Chen, 2009; Deng et al., 2020; C. W. Huang et al., 2017).

The total inefficiency of each observation can be disaggregated as the ratio of the slack of each input and output divided by its absolute (Deng et al., 2020; Wang et al., 2020). Considering that inefficient hotels' input redundancies and output deficits can be measured in terms of slack, we define the *k*-th input inefficiency as the ratio of input slack (s_k^-) to current input $\left(x_{k0}\right)$ and the *q*-th output inefficiency as the ratio of output slack $\left(s_q^+\right)$ to current output $\left(y_{q0}\right)$. The expressions for input and output inefficiencies are as follows:

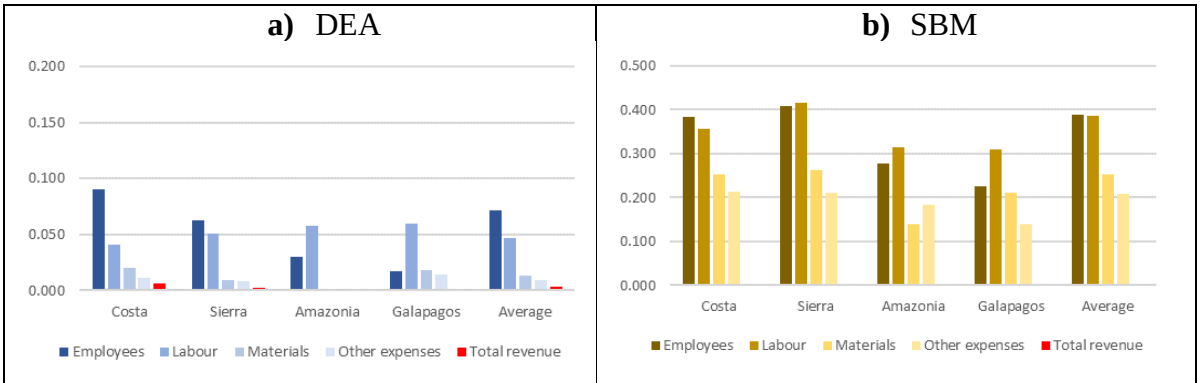
$$Inefx_k = s_k^- / x_{k0}, k = 1,2,3,4,5$$

$$Inefy_q = s_q^+ / y_{q0}, q = 1,2 \qquad [14]$$

Figure 14 compares the global average inefficiencies (2007-2017) from slacks by using DEA and SBM methods (not the bootstrapped, for simplicity) and the four Ecuadorian regions, disaggregated by inputs and outputs (see Appendix, Table A4).

Outstandingly, inefficiencies obtained by the SBM method are higher than those obtained by DEA for any input. While the levels of inefficiencies under the DEA model (Figure 14a) are below 0.10, under the SBM procedure (Figure 14b) they are higher than 0.20.

Figure 14. Regional comparison of slack global average inefficiencies by DEA and SBM methods.

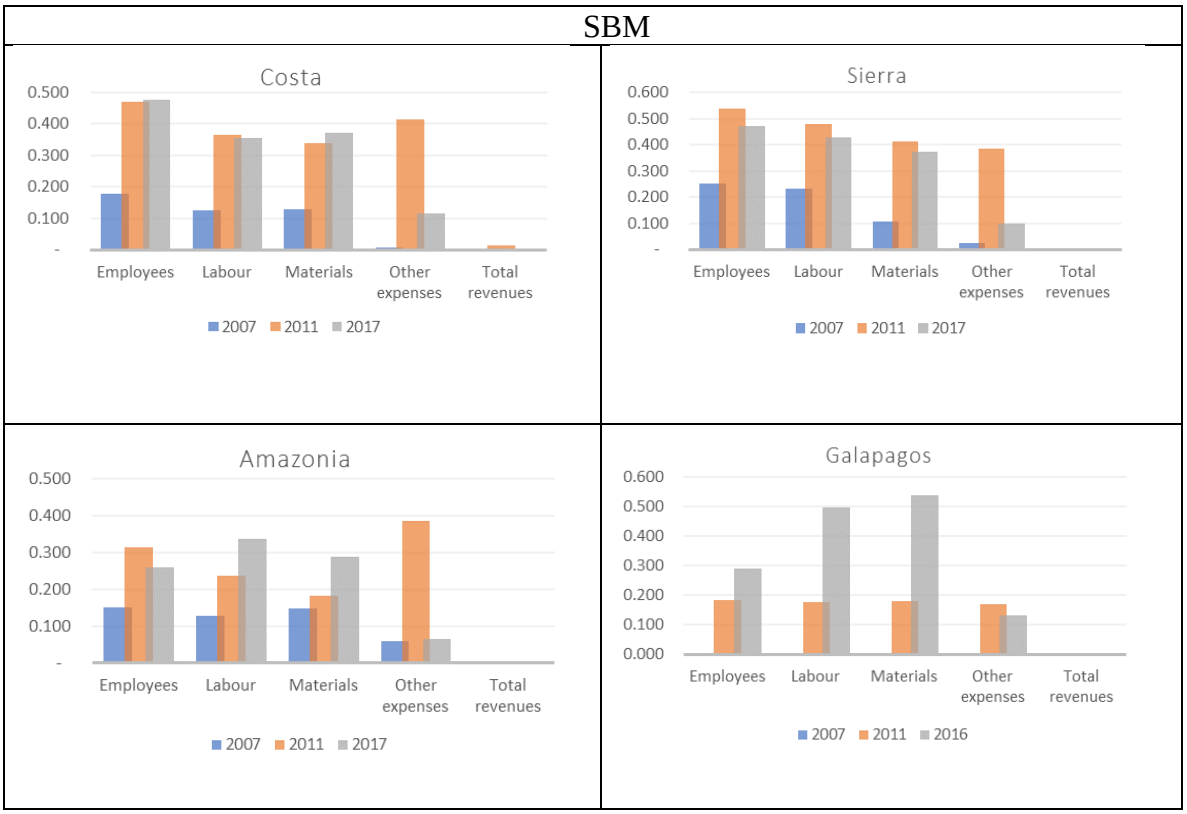


Notes: Employees, Labor, Materials, and Other expenses are inputs; Total revenue is one output.

Notably, inefficiencies come from inputs: employees and labor inefficiencies are higher than material and other expenses, while total revenue tends to have zero inefficiencies.

Next, we assess the inefficiencies over time in Figure 15, focusing on SBM results (see Appendix, Table A5 for details). It is interesting to note that, generally, input inefficiencies tend to increase over time in all regions. It indicates that hotels in these regions should better control resources, especially labor-related ones.

Figure 15. Evolution of regional inefficiencies in the SBM procedure.



5.5.3. Determinants of efficiency

The effects of covariates (exogenous variables) on efficiency are evaluated using the linear regression model, which is stated as follows:

$$Efficiency_i = \beta' x_i + e_i, i = 1, 2, ..., NT \quad [15]$$

where $Efficiency_i$ is the previously estimated DEA and SBM efficiency scores, x_i is a column vector of explanatory variables (including one for the constant term), β' is a term with a standard deviation equal to σ_e.

Results are shown in Table 19, distinguishing four models for efficiency determinants. β' and σ_e were estimated by Simar and Wilson's (2007) procedure based on truncated regression for radial DEA methods (using maximum likelihood and 2000 bootstrap simulations performed for each efficiency score), and we used Tobit's censored regression for non-radial SBM methods.

In general, we distinguish two results.

First, efficiencies estimated by bootstrap methods show differences from their non-bootstrap counterparts. For example, more regression coefficients are statistically significant in bootstrap-DEA than DEA, but are also greater than DEA coefficients. In the case of bootstrap-SBM, regression coefficients tend to be lower than SBM in absolute value, but the number of coefficients statistically significant is similar. In both cases, we can conclude that using average estimates from bootstrap to avoid the uncertainty of efficiency score calculations led to different results that hotel managers can use, especially bootstrap-SBM results, which reflect a more significant impact on efficiency.

Second, we can see that the coefficients for regulation, financial, and economic hotel characteristics are statistically significant across the four models. For example, the IFRS coefficient shows a negative coefficient and is statistically significant at a 1% level for all models. That indicates that the effect of IFRS adoption based on accounting negatively impacted efficiency measures. Karadag (2010) pointed out that IFRS adoption effects are transitory and related to the ownership and liability structure. Also, Koufodontis et al. (2021) considered that hotel managers perceive advantages in IFRS adoption as a function of tourism development (macroeconomic factor) and as a function of their legal structure and category (microeconomic factors).

The results of labor reform exhibit positive coefficients with a 5% and 1% significance level for non-bootstrap and bootstrap models, respectively. We interpret that hotel firms were able to eventually adapt by taking advantage of the economic growth during the labor reform

implementation period. The existing literature consensus indicates that increasing hotel spending to professionalize staff improves productivity through service quality (Aissa and Goaied, 2016; Denvir and McMahon, 1992). Therefore, labor reform could be a great opportunity that brings significant benefits, such as improving service continuity and quality, increasing customer satisfaction, and reducing hiring and training costs. In addition, it facilitates investment in personnel development to generate more qualifications and efficiency. However, legal and competitive labor conditions differ from region to region or country to country. For example, Knox and Nickson (2007) found that labor regulation in Australia benefits the luxury hotel sector through sophisticated negotiations with unions.

The coefficients for the crisis period were positive and statistically significant at 1% in all four models. These results could be unexpected and different from other studies. For example, Parte-Esteban and Alberca-Oliver (2015) reported decreases in hotel efficiency during the financial crisis in Spain. Furthermore, Cordero and Tzeremes (2017), studying hotel productivity growth in the Balearic and Canary Islands, concluded that productivity was affected explicitly in the worst years of the crisis. However, in our case, efficiencies began to decline significantly from 2011 onwards without recovering after that (see Figure 11).

Economic variables are also essential to describe the efficiency of Ecuadorian hotels. For example, the operative return coefficients were statistically significant at 1% and positively influenced efficiency. It shows that increasing operating returns improves efficiency. Therefore, hotel managers could look in-depth at cost and expense management to implement adjustments that reduce inefficiencies. Our results are consistent with those found by Parte-Esteban and Alberca-Oliver (2015) when analyzing the efficiency of the Spanish hotel industry.

The coefficients for debt leverage negatively affect efficiency and are statistically significant at 1% or 5% levels in three models but not in the DEA model. This result is coherent with the fact that excessive debt leverage can lead to inefficiency due to higher financing costs (Stulz, 1990; Warner, 1977). However, it is also worth noting that using debt promotes efficiency by imposing constraints on managers driving efficiency, according to

Guo et al. (2021). For example, the obligation to meet debt payments should reduce problems of overinvestment or overspending.

Table 19. Determinants of technical efficiency using the Simar and Wilson (DEA and Bootstrap DEA) and Tobit (SBM) procedures.

Variables	DEA	Bootstrap DEA	SBM	Bootstrap SBM
Regulatory and crisis variables				
IFRS adoption (2010-2012)	**-0.0773*** **	**-0.0797*** **	**-0.0750*** **	**-0.0801*** **
	(0.0145)	(0.0134)	(0.0183)	(0.0147)
Labor reform (2008-2009)	**0.0495** **	**0.0562*** **	**0.0590** **	**0.0572*** **
	(0.0218)	(0.0192)	(0.0235)	(0.0185)
Crisis period (2007-2008)	**0.0964*** **	**0.1364*** **	**0.0929*** **	**0.0813*** **
	(0.0248)	(0.0222)	(0.0262)	(0.0205)
Financial and economic variables				
Operative return	**0.515*** **	**0.376*** **	**0.362*** **	**0.430*** **
	(0.0635)	(0.0564)	(0.0913)	(0.0715)
Debt leverage	0.00357	**-0.0510** **	**-0.130*** **	**-0.0938** **
	(0.0280)	(0.0253)	(0.0475)	(0.0367)
Market share	**4.149*** **	**1.121** **	**3.562** **	0.526
	(0.893)	(0.475)	(1.475)	(0.798)
Age	-0.0008	**-0.0014*** **	**-0.0063*** **	**-0.0042*** **
	(0.0006)	(0.000503)	(0.00169)	(0.00112)
Large assets	**0.0521** **	**0.0582*** **	0.0505	0.0425
	(0.0209)	(0.0174)	(0.0335)	(0.0261)
Listed hotels	-0.0112	**0.0640** *	**0.132** *	**0.112** **
	(0.0558)	-0.0356	(0.0709)	(0.0511)
Foreign capital	-0.0279	-0.0228	-0.0101	-0.0180
	(0.0196)	(0.0168)	(0.0608)	(0.0380)
Control variables				
Category	Yes	Yes	Yes	Yes
Legal structure	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Constant	**0.620*** **	**0.679*** **	**0.649*** **	**0.606*** **
	(0.0468)	(0.0465)	(0.148)	(0.0959)
σ_e	**0.133*** **	**0.141*** **	**0.1846*** **	**0.1589*** **
	(0.0046)	(0.0044)	(0.0060)	(0.0044)
Observations	600	823	824	824

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Bold numbers indicate that coefficients are statistically significant at the conventional levels.

The market share coefficient shows a positive effect on efficiency, and it is statistically significant at 1% or 5% levels in three models, but not the bootstrap-SBM model. Our result is in line with the empirical literature. For example, (Barros and Dieke, 2008) found a similar effect in a smaller sample of African hotels.

Concerning large assets, the coefficients were positive and statistically significant only for DEA and bootstrap-DEA models at 5% and 1%, respectively. It means larger hotels are more efficient than medium and small ones in Ecuador, but not under SBM procedures. Our result is similar to Assaf and Cvelbar (2010) but differs from Parte-Esteban and Alberca-Oliver (2015). The latter authors concluded that large hotels with high indebtedness are less efficient. Interestingly, size does not represent a differentiator influencing efficiency for the slack-based models (SBM and Bootstrap SBM). That means that variable slacks can be proportional to the size of the Ecuadorian hotels. Another important result is the listed coefficients, which were positive and statistically significant at 10% for bootstrap-DEA and SBM models and at 5% for bootstrap-SBM. This result is consistent with the findings of Honma and Hu (2012) in Japanese hotels, among others.

Concerning age, coefficients were negative and statistically significant at 1% in bootstrap-DEA and SBM models. These results contradict Assaf and Cvelbar's (2010) findings in the Slovenian hotel industry, which report a positive relationship. However, Wang et al. (2006) found no significant effect in Taiwanese hotels. Finally, the coefficient for foreign ownership was not statistically significant. However, previous studies using this variable have shown that it positively and significantly influenced efficiency (Kim, 2011; Zhang et al., 2020).

Chapter 6. Conclusions

The main objective of this Doctoral Thesis was to analyze corporate financial management in Ecuador through econometric methods applied selectively to companies in the productive sector in general, to private banks, and specifically to the hotel sector. The study was delimited temporally to the period 2007-2017 in a context characterized by the same public administration which promoted various legal reforms, from a new constitution from which codes of several types were derived to other rules of application to the business sector, among others.

Three specific objectives were proposed from the perspective of this differentiated context, as well as the main objective. The first aimed to identify the determinants that affect the capital structure of the productive business sector, contrasting companies listed and unlisted in the stock market. The second objective focused on measuring the efficiency of private banks in Ecuador, considering multiple inputs and identifying determinants that explain the variability of inefficiencies over time. The third objective consisted of analyzing the efficiency behaviour of the hotel sector based on various products and factors of production, as well as examining its level of performance by contrasting the four Ecuadorian regions. The specificity of the objectives attempts to bring the thesis's content closer to the doctoral program's central axes.

Each specific objective led to the use of different econometric techniques. To develop the first objective, we start from a general dynamic panel data model based on a *p*-order autoregressive process incorporating rigorously exogenous and endogenous variables as regressors. In this case, we used two GMM-type estimators, one applicable to data sets in numerous panels and few periods and the other to obtain a more efficient estimation of the parameters. The model was validated by applying a Fisher-type unit root test, which showed that the panels were stationary.

The main conclusion from this objective's results is that the companies studied use a partial adjustment mechanism to determine their capital structure. Consequently, the level of leverage observed in a current period depends on that used in the previous period (persistence).

To achieve the second objective, we estimate the efficiency of private banks from two approaches described in separate chapters, considering multiple inputs and outputs. In the first one, we use the parametric stochastic frontier methodology (SFA) of translog type with output-oriented distance function in a Bayesian framework and profitability approach. This model identifies unobserved technological heterogeneity and time-varying efficiency dependent on other banking and economic factors. We estimate the panel data model using a random parameter model based on the results obtained.

In the second approach, we applied non-parametric methodologies such as data envelopment analysis (DEA), using both radial (BCC) and non-radial (SBM) measures. In the second stage, we estimate the effects of some covariates on the efficiencies obtained in the SBM models, applying a censored Tobit regression with maximum likelihood. The particularity of this approach is that we include undesirable outputs LLP and NPL.

As a outstanding conclusion, we note evidence of unobserved heterogeneity across banks and time-varying inefficiencies. On the other hand, large banks tend to be more efficient than medium and small banks.

Regarding the third objective, we estimated the efficiencies with a nonparametric mathematical programming approach for estimating frontiers with radial (DEA) and non-radial (SBM) methods, similar to the second approach of objective two. In the second stage, we analyze the effect of several determinants on the hotel efficiencies in Ecuador obtained in the different models of the first stage. For this, we apply the Simar and Wilson procedure based on truncated regression for the radial DEA methods, while for the non-radial SBM methods, we use Tobit's censored regression.

The major conclusion of the third objective is that the estimation of inefficiencies in the hotel sector tends to increase over time and is more pronounced when measured with non-radial models.

Next, we present the specific conclusions of the results obtained, described in the previous chapters, and explain the more important results.

6.1 Target Leverage and Determinants of Firms' capital structure in Ecuador

Ecuador is an emerging country where to date little research has been conducted concerning issues related to financial management. However, policymakers are seeking to promote development strategies to increase domestic and foreign private investment.

This chapter investigates the determinants of capital structure in Ecuadorian firms. Empirical evidence shows that the impact produced by these determinants varies according to the business context of each country. The present study contributes to the scientific literature in this field by determining the quantitative impact of the factors considered. The results obtained are also analysed in qualitative terms. This two-fold approach highlights the specific ways in which Ecuadorian companies obtain corporate finance.

The panel data method employed, and the dynamic panel models generated show that the companies in our study sample make use of a partial adjustment mechanism in determining their capital structure. Thus, the present leverage depends on that employed in the previous period (persistence).

Several panel data models were used to test hypotheses regarding the lagged leverage variables. These models estimated the effects of the determinants of total leverage and long-term leverage, for both listed and non-listed companies. According to the results obtained, the Pecking-order theory provides a closer fit to the situation examined than the Trade-off theory, for both listed and non-listed companies.

Overall, our study results suggest that the use of long-term leverage in Ecuadorian companies is low relative to equity capital. Therefore, it is questionable whether company growth can be supported by external long-term financing, which places a brake on development. Our analysis provides valuable insights for investors, financiers, and government officials regarding the characteristics of capital structure in Ecuador, including the differences between listed and non-listed firms.

Two limitations to the present study should be acknowledged: a) the incomplete period of the information for some companies in the sample, as well as the difficulties of access to other data on other aspects that could be determinants of capital structure; b) the specific contextual differences of each industry sector. Overcoming this problem would enable a more specific understanding of the issues addressed and help avoid generalisations regarding the conditions of access to financing and firms' approaches to capital structure.

Finally, it should be noted that the business environment in Ecuador requires greater harmonisation between the productive and the financial sectors. In particular, it is essential to transfer the immediacy of short-term financing to strategies aimed at capital structure. With this, Ecuador could aspire to a more rapid development of its business sector.

6.2 Heterogeneity and time-varying efficiency in the Ecuadorian banking sector. An output distance stochastic frontier approach

This chapter extends the existing literature on bank efficiency in two ways. Firstly, we use the output distance translog stochastic frontier specification in a Bayesian framework to model time-varying efficiency and technological unobserved heterogeneity. To do this, we can relax the same production technology assumption for all banks, considering random coefficients to account for technological heterogeneity. Feng and Zhang (2014) found that failing to consider banks' unobserved technology heterogeneity could provoke a misleading ranking and mismeasured RTS. Secondly, we analyze the role of several determinants affecting time-varying efficiency in a one-step output distance Bayesian estimation procedure.

Chapter 6

Our empirical analysis is based on the Ecuadorian banking industry, a dollarized and emergent economy in Latin America. We assessed the effect of banking regulation and other determinants on efficiency during a period of significant country restructuration of their economy. Data was obtained from the Superintendency of Banks website.

The main results obtained are the following: first, our study revealed time-varying technical efficiency and unobserved heterogeneity in the Bayesian model, and transient efficiency remains slightly constant over time in median terms; second, the foreign ownership of the bank is the only important factor explaining inefficiency. Still, variables related to the Central Bank policy regulation and internal banking factors, such as operating profitability, do not affect time-varying efficiency.

The method and results presented in this paper have interesting theoretical and policy implications. On the one hand, this article provides an overview of the output distance function stochastic frontier model as a tool to disentangle overall efficiency between transient efficiency and unobserved heterogeneity using random parameter models in a Bayesian framework, but considering as a novelty, the modeling of the conditional mean inefficiency based on exponential distribution. Therefore, applying the method described could help managers identify banks that present inefficiencies, enabling these banks to be ranked, determining the impact of unobserved heterogeneity, and estimating RTS.

On the other hand, this approach could offer important information for bank managers about short-term implications for the industry.

Bank managers are fundamental to efficiently running operations and need various skills (e.g., customer relations, reputation management, revenue and budget management, and familiarity with the latest bank technologies). Therefore, sources of inefficiency must be identified so that bank managers can redress deficiencies and thus enhance performance. Our results show that transient efficiency is a factor that varies over time, and consideration of this question can help Ecuadorian bank managers respond appropriately to year-by-year changes. One interesting factor is that managers of Ecuadorian banks should improve their management compared to foreign banks. Concerning size, although large banks tend to

increase market concentration, their financial performance was lower than that of medium-sized banks at the end of the period studied. This result suggests that managers should analyze the effectiveness of operating expenses and revenue targets by product or service type. However, our results do not show favorable evidence of other environmental factors affecting efficiencies, such as bank reserve requirements, age, and operating profitability. In this sense, we cannot conclude anything about the design of specific strategies based on these results by bank managers.

Certain limitations to the present study should be acknowledged. On the one hand, the sample size of banks is low despite the number of periods being large enough. Therefore, the study could include other Ecuadorian financial institutions, such as commented in Section 3.2, given that new regulations may focus on boosting state banking competitiveness. It could also consider the inclusion of credit unions whose size represents a similar or more extensive market share than certain banks, without ignoring the different legislation for each type of financial institution. On the other hand, other econometric approaches using the random parameters model in the Bayesian framework could be introduced. For example, we could assume other distributions for inefficiency terms such as the truncated-normal, which allow us to model conditional mean over time depending on covariates.

Future research can develop models that disentangle bank efficiency between transient (non-systematic) and persistent (systematic) parts. The omission of this issue can produce a biased estimate of overall inefficiency, especially if persistent inefficiency and unobserved heterogeneity (both or not) are present (Colombi et al., 2014). Besides, if these two efficiencies were omitted from the analysis, it might be impossible to formulate effective policy measures.

6.3 Assessing the effects of loan loss provisions and non-performing loans in bank's inefficiency

This chapter revisits the analysis of bank efficiency, separating good and bad outputs. Our work differs from previous contributions in the field by assessing the effects of loan loss

provisions (LLP) and non-performing loans (NPLs) on a bank's inefficiency as two measures of undesirable outputs.

To do this, we employ the SBM approach, which is non-radial and allows us to use non-oriented technology and will enable us to use undesirable outputs. The empirical analysis uses data from Ecuadorian banks from 2007 to 2017 under the assumption of variable returns to scale.

The results indicate that, in general, efficiencies are high in both approaches (where some banks are fully efficient). Still, using LLPs as a bad output can overestimate bank efficiencies in the presence of NPLs. Besides, based on the slacks of the SBM model, results show NPL inefficiencies are higher than LLP inefficiencies. Therefore, this paper shows that NPLs could be a better bad output than LLPs to estimate bank efficiency.

From another perspective, the size classification shows that banks can achieve total efficiencies despite this characteristic. However, the lowest efficiencies correspond to some medium and small banks.

We tested the effect of efficiency determinants by applying the censored Tobit regression procedure, both with LLP and NPL models. For this purpose, we used a set of variables to find mixed results. First, Age, ROA, and market share were significant for both models. While other variables such as linear time trend, commercial business, non-debt tax shield (NDTS), and stock market were significant for Model 1. For Model 2, were significant also the variables liquidity risk and ownership.

Based on the results, we consider that, in general, regulatory norms in Ecuador have a favorable impact on efficiency. However, the rule regarding reserves for NPLs seems excessive, negatively influencing efficiency through the capital requirement (capital ratio). On the other hand, the positive impact on ROA, which is supposed to be driven by the same banking regulation, stands out.

The results lead to interesting reflections. First, banking regulation in Ecuador promotes bank deepening by controlling interest rates and seeks to reduce the occurrence of bad loans through capital reserves. Second, that bank management in Ecuador can adapt to regulatory standards and remain highly efficient. Third, less efficient banks can look at the financial indicators of efficient banks and try to improve their performance.

Some limitations should be recognized. On the one hand, for example, the number of banks and periods could be extended to include other non-commercial banks working on the analyzed period. On the other hand, other determinants should be explored to explain efficiencies, such as credit risk and liquidity.

Future research could use other efficiency methods to compare results, such as the Russell directional distance function, or implement a parametric stochastic frontier approach. For example, some models can individually compute the efficiency of inputs and outputs.

6.4 Assessing the performance of the Ecuadorian hotel industry under a regulatory period

This chapter analyzes the operational efficiency of the hotel industry in an emerging economy in Latin America: Ecuador. The study is framed in a political, economic, and governmental stability period from 2007 to 2017. The data corresponds to Ecuadorian hotel companies' financial information published by SUPERCIAS.

Theoretical implications

This study analyzes the role of labor reform, IFRS adoption, and other economic and financial characteristics of hotels on the efficiency of Ecuadorian hotels, comparing efficiencies obtained by different non-parametric methods such as radial (DEA) and non-radial (SBM). As a novelty in hotel efficiency studies, we also include the comparison between bootstrap-DEA and bootstrap-SBM to account for estimating the unknown distribution of the efficiency scores. We apply these models with an input-oriented approach, assuming managers control inputs. The Kruskal-Wallis test shows significant differences in the estimated efficiency.

Managerial implications

The management implications of our results are varied. Several factors affecting the efficiency of Ecuadorian hotels have been analyzed using the Simar-Wilson procedure (for

the efficiencies estimated under DEA models) and Tobit regression (for the efficiencies obtained by the SBM models).

According to the results, managers could develop hotel management strategies by identifying the factors that affect efficiency and reasoning about their implications on the fundamental management objectives. Therefore, this article provides the following valuable information for the lodging sector in Ecuador:

first, given the adverse effects of IFRS adoption, hotel managers should question whether the performance objectives align with each hotel's financial reality. For example, they must ensure that the hotel operation adds value to the firm. Regarding labor reform's positive effects, hotel companies must choose between unrepeatable temporary or permanent contracts (Knox and Nickson, 2007). The first implies staff turnover, possibly lowering the quality of service, and increasing training costs (Denvir and McMahon, 1992); the second leads to the risk of permanent labor expenses in low occupancy seasons or increased competition. The hotel managers must evaluate the sustainability of the contracting model in the medium and long term.

Second, managers can improve efficiency by implementing policies to enhance revenues and competitiveness (market share) in the hotel industry, for example, by sharing knowledge and experiences to strengthen the tourist destination's competitiveness (Rodríguez-Victoria et al., 2017). Other examples include the specialization by market segment that identifies customers' service quality expectations and facilitates the promotion of a diversified offer based on individual strengths and resources. Therefore, organizing the hotel sector under a cluster model for competitiveness can help improve the participants' efficiency (Camisón and Forés, 2015).

Third, hotel managers can focus on some interesting financial characteristics. On the one hand, the significance of the operative return factor shows that the optimization of costs and expenses in terms of revenue generation is of paramount importance for Ecuadorian hotel management. On the other hand, the impact of debt leverage on hotel performance depends on several factors, such as the hotel's financial strength, market conditions, management abilities, and overall debt structure. Hence, hotel managers must have financial flexibility strategies (such as using equity financing) to moderate debt leverage when it negatively

affects the hotel's efficiency (Aissa and Goaied, 2016). Achieving the right balance between debt leverage and operational needs is crucial for hotels to optimize efficiency. It can be difficult during economic downturns or periods of low occupancy, limiting the hotel's ability to improve efficiency and maintain competitiveness (Vivel-Búa et al., 2018). Finally, listed hotels could have an advantage over unlisted hotels in two ways. First, listed hotels have access to funds to invest in improving service quality. Second, listed companies acquire prestige because they can demonstrate their managerial capabilities. Managers of unlisted hotels should identify critical drivers that favor listed hotels. For example, explore whether the costs and expenses associated with listing can be amortized over the medium to long term in exchange for access to lower-cost financing.

Some aspects could explain the negative impact of age on efficiency, among others: one is that older hotels require higher maintenance costs, and the other is that the growing offer represents new establishments that are more attractive to guests. These aspects could force older hotels to reduce occupancy rates or increase investments to improve and modernize infrastructure and equipment.

Lastly, it is necessary to recognize some limitations, for example, the quantity and quality of inputs and outputs and the sample composition. Regarding the sample, it does not include single-person lodging establishments due to barriers to access to information. In addition, the majority of the sector's corporate enterprises are short-lived. These two aspects limit the possibilities of improving or extending the temporal and geographical scope of the research. However, it is possible to incorporate other factors and determinants if resources are available to obtain them, such as collecting data through surveys.

References

Ablanedo-Rosas, J. H., Rubio, I., Chen, J. and Ruiz-Torres, A. J. (2023). COVID-19 impact on the operational efficiency of a downtown hotel. *Anatolia*, *34*(2), 130–143. https://doi.org/10.1080/13032917.2021.1997774

Achi, A. (2021). Efficiency and its determinants in the Algerian banks: network data envelopment analysis and partial least squares regression. *International Journal of Productivity and Performance Management*. https://doi.org/10.1108/IJPPM-07-2021-0407

Adair, P. and Adaskou, M. (2015). Trade-off-theory vs. pecking order theory and the determinants of corporate leverage: Evidence from a panel data analysis upon French SMEs (2002-2010). *Cogent Economics & Finance*, *3*(1), 1–12. https://doi.org/10.1080/23322039.2015.1006477

Adams, R. M., Berger, A. N. and Sickles, R. C. (1999). Semiparametric approaches to stochastic panel frontiers with applications in the banking industry. *Journal of Business and Economic Statistics*, *17*(3), 349–358. https://doi.org/10.1080/07350015.1999.10524823

Agyei, J., Sun, S. and Abrokwah, E. (2020). Trade-Off Theory Versus Pecking Order Theory: Ghanaian Evidence. *SAGE Open*, *10*(3), 1–13. https://doi.org/10.1177/2158244020940987

Aissa, B. S. and Goaied, M. (2016). Determinants of Tunisian hotel profitability: The role of managerial efficiency. *Tourism Management*, *52*, 478–487. https://doi.org/10.1016/j.tourman.2015.07.015

Aivazian, V. A., Ge, Y. and Qiu, J. (2005). The impact of leverage on firm investment: Canadian evidence. *Journal of Corporate Finance*, *11*(1–2), 277–291. https://doi.org/10.1016/S0929-1199(03)00062-2

AKERLOF, G. A. (1978). THE MARKET FOR "LEMONS": QUALITY UNCERTAINTY AND THE MARKET MECHANISM**The author would especially like to thank Thomas Rothenberg for invaluable comments and inspiration. In addition he is indebted to Roy Radner, Albert Fishlow, Bernard Saffran, William . In *Uncertainty in Economics* (pp. 235–251). https://doi.org/10.1016/b978-0-12-214850-7.50022-x

Akkaya, O. (2017). BANKING EFFICIENCY IN THE EUROZONE. *Yönetim ve Ekonomi Araştırmaları Dergisi*, 177–187. https://doi.org/10.11611/yead.373457

Al-Najjar, B. (2011). The inter-relationship between capital structure and dividend policy: Empirical evidence from jordanian data. *International Review of Applied Economics*,

25(2), 209–224. https://doi.org/10.1080/02692171.2010.483464

Alcock, J. and Steiner, E. (2017). The interrelationships between REIT capital structure and investment. *Abacus*, *53*(3), 371–394. https://doi.org/10.1111/abac.12113

Alipour, M., Mohammadi, M. F. S. F. S. and Derakhshan, H. (2015). Determinants of capital structure: An empirical study of firms in Iran. *International Journal of Law and Management*, *57*(1), 53–83. https://doi.org/10.1108/IJLMA-01-2013-0004

Allen, D. E. (1993). The pecking order hypothesis: Australian evidence. *Applied Financial Economics*, *3*(2), 101–112. https://doi.org/10.1080/758532828

Allen, K. (1999). DEA in the ecological context — An overview. In *Data Envelopment Analysis in the Service Sector* (pp. 203–235). Deutscher Universitätsverlag, Wiesbaden. https://doi.org/10.1007/978-3-663-08343-6_11

Altman, E. I. (1968). Financial ratios, discriminant anlysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K. and Suvas, A. (2017). Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model. *Journal of International Financial Management and Accounting*, *28*(2), 131–171. https://doi.org/10.1111/jifm.12053

Anderson, R. I., Fok, R. and Scott, J. (2000). Hotel industry efficiency: An advanced linear programming examination. *American Business Review*, *18*(1), 40–48. https://www.proquest.com/docview/216312569

Andrieş, A. M. and Cocriş, V. (2010). A comparative analysis of the efficiency of Romanian banks. *Romanian Journal of Economic Forecasting*, *13*(4), 54–75. https://www.scopus.com/inward/record.uri?eid=2-s2.0-79951486703&partnerID=40&md5=edfd9623d76340629792f5377dd99448

Antoniou, A., Guney, Y. and Paudyal, K. (2016). The Determinants of Capital Structure: Capital Market-Oriented versus Bank-Oriented Institutions. *Journal of Financial and Quantitative Analysis*, *43*(1), 59–92. https://doi.org/https://doi.org/10.1017/S0022109000002751

Arbelo, A., Arbelo-Pérez, M. and Pérez-Gómez, P. (2021). Heterogeneity of Resources and Performance in the Hotel Industry. *Journal of Hospitality and Tourism Research*, *45*(1), 68–89. https://doi.org/10.1177/1096348020944450

Ashrafi, A., Seow, H. V., Lee, L. S. and Lee, C. G. (2013). The efficiency of the hotel industry in Singapore. *Tourism Management*, *37*, 31–34. https://doi.org/10.1016/j.tourman.2012.12.003

Assaf, A., Barros, C. P. and Josiassen, A. (2010). Hotel efficiency: A bootstrapped

metafrontier approach. *International Journal of Hospitality Management*, *29*(3), 468–475. https://doi.org/10.1016/j.ijhm.2009.10.020

Assaf, A. and Cvelbar, L. K. (2010). The performance of the Slovenian hotel industry: Evaluation post-privatisation. *International Journal of Tourism Research*, *12*(5), 462–471. https://doi.org/10.1002/jtr.765

Assaf, A. G. and Agbola, F. W. (2011). Modelling the performance of Australian hotels: A DEA double bootstrap approach. *Tourism Economics*, *17*(1), 73–89. https://doi.org/10.5367/te.2011.0027

Assaf, A. G. and Barros, C. P. (2013). A global benchmarking of the hotel industry. *Tourism Economics*, *19*(4), 811–821. https://doi.org/10.5367/te.2013.0230

Assaf, A. G. and Magnini, V. (2012). Accounting for customer satisfaction in measuring hotel efficiency: Evidence from the US hotel industry. *International Journal of Hospitality Management*, *31*(3), 642–647. https://doi.org/10.1016/j.ijhm.2011.08.008

Assaf, G. A., Matousek, R. and Tsionas, E. G. (2013). Turkish bank efficiency: Bayesian estimation with undesirable outputs. *Journal of Banking and Finance*, *37*(2), 506–517. https://doi.org/10.1016/j.jbankfin.2012.09.009

Awaliyah, S., Negoro, D. A., Syah, T. Y. R. and Bertuah, E. (2021). Impact of Empiris Profitability, Growth, Size Firm, Tangibility on Capital Structure of the Hotel Industry. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3760927

Ballescá, M. (2007). La banca extranjera en América Latina: resultado de su desempeño. *Espiral*, *XIV*(40), 123–156. https://www.scielo.org.mx/scielo.php?pid=S1665-05652007000100005&script=sci_arttext

Baltensperger, E. and Dermine, J. (1986). The Role of Public Policy in Insuring Financial Stability: A Cross-Country, Comparative Perspective. In *INSEAD* (No. 33). INSEAD.

Bandyopadhyay, A. and Barua, N. M. (2016). Factors determining capital structure and corporate performance in India: Studying the business cycle effects. *Quarterly Review of Economics and Finance*, *61*, 160–172. https://doi.org/10.1016/j.qref.2016.01.004

Banker, R. D., Charnes, A. and Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9), 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

Banker, R. D., Huang, R. and Li, Y. (2014). Do Accounting Standards Matter for Firm Productivity? Evidence from Mandatory IFRS Adoption. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2429121

Bansal, R. and Singh, D. (2021). Efficiency drivers of insurers in GCC: an analysis incorporating company-specific and external environmental variables. *Cogent Economics & Finance*, *9*(1). https://doi.org/10.1080/23322039.2021.1922179

References

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barros, C. P. (2005a). Measuring efficiency in the hotel sector. *Annals of Tourism Research*, *32*(2), 456–477. https://doi.org/10.1016/j.annals.2004.07.011

Barros, C. P. (2005b). Evaluating the efficiency of a small hotel chain with a Malmquist productivity index. *International Journal of Tourism Research*, *7*(3), 173–184. https://doi.org/10.1002/jtr.529

Barros, C. P. and Alves, F. (2004). Productivity in the Tourism Industry. *International Advances in Economic Research*, *10*(3), 215–225. https://www.proquest.com/docview/217174248

Barros, C. P., Botti, L., Peypoch, N. and Solonandrasana, B. (2011). Managerial efficiency and hospitality industry: The Portuguese case. *Applied Economics*, *43*(22), 2895–2905. https://doi.org/10.1080/00036840802600145

Barros, C. P. and Dieke, P. (2008). Technical efficiency of African hotels. *International Journal of Hospitality Management*, *27*(3), 438–447. https://doi.org/10.1016/j.ijhm.2007.11.004

Barros, C. P., Leão, E. R., Macanda, N. P. J. and Mendes, Z. (2016). A Bayesian Efficiency Analysis of Angolan Banks. *South African Journal of Economics*, *84*(3), 484–498. https://doi.org/10.1111/saje.12124

Barros, C. P., Managi, S. and Matousek, R. (2012). The technical efficiency of the Japanese banks: Non-radial directional performance measurement with undesirable output. *Omega*, *40*(1), 1–8. https://doi.org/10.1016/j.omega.2011.02.005

Barros, C. P. and Williams, J. (2013). The random parameters stochastic frontier cost function and the effectiveness of public policy: Evidence from bank restructuring in Mexico. *International Review of Financial Analysis*, *30*, 98–108. https://doi.org/10.1016/j.irfa.2013.06.006

Baskin, J. (1989). An Empirical Investigation of the Pecking Order Hypothesis. *Financial Management*, *18*(1), 26–35. https://doi.org/10.2307/3665695

Battese, G. E., Prasada Rao, D. S. and O'Donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis*, *21*(1), 91–103. https://doi.org/10.1023/B:PROD.0000012454.06094.29

Baxter, N. D. (1967). Leverage, Risk of Ruin and the Cost of Capital. *The Journal of Finance*, *22*(3), 395–403. https://www.jstor.org/stable/2978892

Benston, G. J. and Kaufman, G. G. (1996). The Appropriate Role of Bank Regulation. *The Economic Journal*, *106*(436), 688–697. http://www.jstor.com/stable/2235577

References

Berger, A. N. and Bonaccorsi Di Patti, E. (2006). Capital Structure and Firm Performance: A New Approach to Testing Agency Theory and an Application to the Banking Industry. *Journal of Banking & Finance*, *30*, 1065–1102. https://doi.org/10.1016/j.jbankfin.2005.05.015

Berger, A. N. and DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, *21*(6), 849–870. https://doi.org/10.1016/S0378-4266(97)00003-4

Berger, A. N., DeYoung, R., Genay, H. and Udell, G. F. (2005). Globalization of Financial Institutions: Evidence from Cross-Border Banking Performance. *SSRN Electronic Journal*, *120*, 23–120. https://doi.org/10.2139/ssrn.203509

Berger, A. N. and Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, *98*(2), 175–212. https://doi.org/10.1016/S0377-2217(96)00342-6

Berger, A. N. and Mester, L. J. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking and Finance*, *21*(7), 895–947. https://doi.org/10.1016/S0378-4266(97)00010-1

Bhattacharya, S., Boot, A. W. A. and Thakor, A. V. (1998). The Economics of Bank Regulation. *Journal of Money, Credit and Banking*, *30*(4), 745–770. https://www.jstor.org/stable/2601127

Bhuyan, B., Patra, S. and Bhuian, R. K. (2021). Measurement and determinants of total factor productivity: evidence from Indian banking industry. *International Journal of Productivity and Performance Management*. https://doi.org/10.1108/IJPPM-06-2019-0256

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Bond, S. (1991). Some tests of specification for panel data:monte carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968

Bonilla, K., Serafim, M. and Bámaca-López, E. (2021). Science Diplomacy in Ecuador: Political Discourse and Practices Between 2007 and 2017. *Frontiers in Research Metrics and Analytics*, *6*(May), 1–17. https://doi.org/10.3389/frma.2021.656969

Booth, L., Aivazian, V., Demirgüç-Kunt, A. and Maksimovic, V. (2001). Capital Structures in Developing Countries. *The Journal of Finance*, *56*(1), 87–130. https://doi.org/10.1111/0022-1082.00320

Bos, J. W. B., Koetter, M., Kolari, J. W. and Kool, C. J. M. (2009). Effects of heterogeneity on bank efficiency scores. *European Journal of Operational Research*, *195*(1), 251–

261. https://doi.org/10.1016/J.EJOR.2008.01.019

Botti, L., Briec, W. and Cliquet, G. (2009). Plural forms versus franchise and company-owned systems: A DEA approach of hotel chain performance. *Omega*, *37*(3), 566–578. https://doi.org/10.1016/j.omega.2007.12.002

Bradley, M., Jarrell, G. A. and Kim, E. H. (1984). On the Existence of an Optimal Capital Structure: Theory and Evidence. *The Journal of Finance*, *39*(3), 857–878. https://doi.org/10.1111/j.1540-6261.1984.tb03680.x

Breitung, J. (2000). The local power of some unit root tests for panel data. *Advances in Econometrics*, *15*, 161–177. https://doi.org/10.1016/S0731-9053(00)15006-6

Brown, J. R. and Ragsdale, C. T. (2002). The competitive market efficiency of hotel brands: An application of data envelopment analysis. *Journal of Hospitality and Tourism Research*, *26*(4), 332–360. https://doi.org/10.1177/109634802237483

Bukair, A. A. A. (2019). Factors influencing Islamic banks' capital structure in developing economies. *Journal of Islamic Accounting and Business Research*, *10*(1), 2–20. https://doi.org/10.1108/JIABR-02-2014-0008

Cabrera-Suárez, I. and Pérez-Rodríguez, J. V. (2021). Bank branch performance and cost efficiency: A stochastic frontier panel data approach. *International Journal of Finance & Economics*, *26*(4), 5850–5863. https://doi.org/10.1002/IJFE.2097

Camisón, C. and Forés, B. (2015). Is tourism firm competitiveness driven by different internal or external specific factors?: New empirical evidence from Spain. *Tourism Management*, *48*, 477–499. https://doi.org/10.1016/j.tourman.2015.01.001

Campoverde, J. A., Flores, G. G., Corone, K. T. and Romero, C. A. (2020). Empirical Evaluation of the Efficiency of Ecuadorian Banking Sector. *Harvard Deusto Business Research*, *9*(1), 20. https://doi.org/10.3926/hdbr.256

Carvallo, O. and Kasman, A. (2005). Cost efficiency in the Latin American and Caribbean banking systems. *Journal of International Financial Markets, Institutions and Money*, *15*(1), 55–72. https://doi.org/10.1016/j.intfin.2004.02.002

Cassar, G. and Holmes, S. (2003). Capital structure and financing of SMEs: Australian evidence. *Accounting and Finance*, *43*(2), 123–147. https://doi.org/10.1111/1467-629X.t01-1-00085

Chaklader, B. and Padmapriya, B. (2021). Impact of cash surplus on firm's capital structure: validation of pecking order theory. *Managerial Finance*, *47*(12), 1801–1816. https://doi.org/10.1108/MF-08-2020-0417

Chakrabarti, A. and Chakrabarti, A. (2019). The capital structure puzzle – evidence from Indian energy sector. *International Journal of Energy Sector Management*, *13*(1), 2–23. https://doi.org/10.1108/IJESM-03-2018-0001

References

Chakraborty, I. (2010). Capital structure in an emerging stock market: The case of India. *Research in International Business and Finance*, *24*(3), 295–314. https://doi.org/10.1016/j.ribaf.2010.02.001

Charnes, A., Cooper, W. W. and Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, J. (2004). Determinants of capital structure of Chinese-listed companies. *Journal of Business Research*, *57*(12 SPEC.ISS.), 1341–1351. https://doi.org/10.1016/S0148-2963(03)00070-5

Chen, L.-J. and Chen, S.-Y. (2011). The influence of profitability on firm value with capital structure as the mediator and firm size and industry as moderators. *Investment Management and Financial Innovations*, *8*(3), 121–129. https://www.scopus.com/inward/record.uri?eid=2-s2.0-81755182756&partnerID=40&md5=e0b1623dc78a9a75bbfd9a39baade7db

Chen, T. H. (2009). Performance measurement of an enterprise and business units with an application to a Taiwanese hotel chain. *International Journal of Hospitality Management*, *28*(3), 415–422. https://doi.org/10.1016/j.ijhm.2008.10.010

Chiang, W. E., Tsai, M. H. and Wang, L. S. M. (2004). A DEA Evaluation of Taipei Hotels. *Annals of Tourism Research*, *31*(3), 712–715. https://doi.org/10.1016/J.ANNALS.2003.11.001

Chittenden, F., Hall, G. and Hutchinson, P. (1996). Small firm growth, access to capital markets and financial structure: Review of issues and an empirical investigation. *Small Business Economics*, *8*(1), 59–67. https://doi.org/10.1007/BF00391976

Choi, I. (2001). Unit root tests for panel data. *Journal of International Money and Finance*, *20*(2), 249–272. https://doi.org/10.1016/S0261-5606(00)00048-6

Chortareas, G. E., Garza-García, J. G. and Girardone, C. (2012). Competition, efficiency and interest rate margins in Latin American banking. *International Review of Financial Analysis*, *24*, 93–103. https://doi.org/10.1016/j.irfa.2012.08.006

Chortareas, G. E., Girardone, C. and Ventouri, A. (2012). Bank supervision, regulation, and efficiency: Evidence from the European Union. *Journal of Financial Stability*, *8*(4), 292–302. https://doi.org/10.1016/j.jfs.2011.12.001

Chortareas, G. and Kapetanios, G. (2009). Getting PPP right: Identifying mean-reverting real exchange rates in panels. *Journal of Banking & Finance*, *33*(2), 390–404. https://doi.org/10.1016/J.JBANKFIN.2008.08.010

Christopoulos, D. K., Lolos, S. E. G. and Tsionas, E. G. (2002). Efficiency of the Greek banking system in view of the EMU: a heteroscedastic stochastic frontier approach. *Journal of Policy Modeling*, *24*(9), 813–829. https://doi.org/10.1016/S0161-

8938(02)00174-6

Chung, K. (1993). Asset characteristics and corporate debt policy: an empirial test. *Journal of Business Finance and Accounting*, *20*(1), 83–98. https://doi.org/https://doi.org/10.1111/j.1468-5957.1993.tb00251.x

Chung, Y. H., Färe, R. and Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*, *51*(3), 229–240. https://doi.org/10.1006/jema.1997.0146

Clarke, G., Cull, R., Peria, M. S. M. and Sánchez, S. M. (2003). Foreign bank entry: Experience, implications for developing economies, and agenda for further research. *World Bank Research Observer*, *18*(1), 25–59. https://doi.org/10.1093/wbro/lkg002

Coelli, T. and Perelman, S. (2000). Technical efficiency of European railways: A distance function approach. *Applied Economics*, *32*(15), 1967–1976. https://doi.org/10.1080/00036840050155896

Coelli, T., Prasada Rao, D. S., O´Donell, C. J. and Battese, G. E. (2005). *An Introduction to Efficiency and Productivity Analysis* (2nd edition). Kluver Academic Publishers.

Coll-Serrano, V., Bolos, V. and Benitez Suarez, R. (2022). *DeaR: Conventional and fuzzy data envelopment analysis* (R Package Version 1.2.5). https://cran.r-project.org/web/packages/deaR/index.html

Colombi, R., Kumbhakar, S. C., Martini, G. and Vittadini, G. (2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis*, *42*(2), 123–136. https://doi.org/10.1007/s11123-014-0386-y

Conner, K. R. (1991). A Historical Comparison of Resource-Based Theory and Five Schools of Thought Within Industrial Organization Economics: Do We Have a New Theory of the Firm? *Journal of Management*, *17*(1), 121–154. https://doi.org/10.1177/014920639101700109

Cordero, J. M. and Tzeremes, N. G. (2017). Evaluating hotel productivity growth in Balearic and Canary islands. *Tourism Economics*, *23*(5), 1146–1154. https://doi.org/10.1177/1354816616683051

Cordero, J. M. and Tzeremes, N. G. (2018). Financial crisis and hotels' labour productivity growth: evidence from Spanish islands. *Applied Economics Letters*, *25*(19), 1376–1382. https://doi.org/10.1080/13504851.2017.1420884

Cruz, M. M. P. (2017). The Operational Efficiency and Sustainability of Selected De Luxe Class Hotels in Metro Manila. *European Journal of Business and Management*, *9*(27), 135–149. https://iiste.org/Journals/index.php/EJBM/article/view/38831

Cueva, D. F., Armas, R., Rojas, D. and Gonzalez, D. (2016). Estructura de capital: Variables micro y macroeconómicas El caso de las empresas manufactureras de Ecuador. *Iberian*

Conference on Information Systems and Technologies, CISTI, *2016-July*. https://doi.org/https://ieeexplore.ieee.org/document/7521625

Czerwonka, L. and Jaworski, J. (2021). Capital structure determinants of small and medium-sized enterprises: evidence from Central and Eastern Europe. *Journal of Small Business and Enterprise Development*, *28*(2), 277–297. https://doi.org/10.1108/JSBED-09-2020-0326

Dammon, R. and Senbet, L. W. (1988). The Effect of Taxes and Depreciation on Corporate Investment and Financial Leverage. *The Journal of Finance*, *43*(2), 357–373. https://doi.org/10.1111/j.1540-6261.1988.tb03944.x

Danquah, M., Barimah, A. and Ohemeng, W. (2013). Efficiency Measurement Using a "True" Random Effects and Random Parameter Stochastic Frontier Models: An Application to Rural and Community Banks in Ghana. *Modern Economy*, *04*(12), 864–870. https://doi.org/10.4236/me.2013.412093

de Bandt, O., Lecarpentier, S. and Pouvelle, C. (2021). Determinants of banks'liquidity: A French perspective on interactions between market and regulatory requirements. *Journal of Banking and Finance*, *124*, 1–18. https://doi.org/10.1016/j.jbankfin.2020.106032

de Jong, A., Kabir, R. and Nguyen, T. T. (2008). Capital structure around the world: The roles of firm- and country-specific determinants. *Journal of Banking & Finance*, *32*(9), 1954–1969. https://doi.org/10.1016/j.jbankfin.2007.12.034

De Jorge, J. and Suárez, C. (2014). Productivity, efficiency and its determinant factors in hotels. *Service Industries Journal*, *34*(4), 354–372. https://doi.org/10.1080/02642069.2013.778977

de Miguel, A. and Pindado, J. (2001). Determinants of capital structure: new evidence from Spanish panel data. *Journal of Corporate Finance*, *7*(1), 77–99. https://doi.org/10.1016/S0929-1199(00)00020-1

DeAngelo, H. and Masulis, R. W. (1980). Optimal capital structure under corporate and personal taxation. *Journal of Financial Economics*, *8*(1), 3–29. https://doi.org/10.1016/0304-405X(80)90019-7

Dell'Ariccia, G. and Marquez, R. (2004). Information and bank credit allocation. *Journal of Financial Economics*, *72*(1), 185–214. https://doi.org/10.1016/S0304-405X(03)00210-1

Deng, Z., Gao, Y., Liang, B. and Morrison, A. M. (2020). Efficiency evaluation of hotel operations in Mainland China based on the superefficiency SBM model. *Tourism Economics*, *26*(2), 276–298. https://doi.org/10.1177/1354816618816787

Denvir, A. and McMahon, F. (1992). Labour turnover in London hotels and the cost effectiveness of preventative measures. *International Journal of Hospitality*

References

Management, *11*(2), 143–154. https://doi.org/10.1016/0278-4319(92)90007-I

Díaz Rodriguez, N. P. D. las M., Mora Pisco, L. L. and Durán Vasco, M. E. (2019). Las bases del cambio de la matriz productiva en Ecuador (2006-2016). *Universidad y Sociedad*, *11*(4), 377–384.

Donaldson, G. (1961). *Corporate debt capacity;a study of corporate debt policy and the determination of corporate debt capacity* (The President and Fellows of Harvard College (ed.)). Harvard University. http://hdl.handle.net/2027/uc1.b4355551

Dong, Y. Z., Hamilton, R. and Tippett, M. (2014). Cost efficiency of the Chinese banking sector: A comparison of stochastic frontier analysis and data envelopment analysis. *Economic Modelling*, *36*, 298–308. https://doi.org/10.1016/j.econmod.2013.09.042

Dragotă, I. M. M., Dragotă, V., Obreja Brasoveanu, L. and Semenescu, A. (2008). Capital structure determinants: A sectorial analysis for the Romanian listed companies. *Economic Computation and Economic Cybernetics Studies and Research*, *1–2*, 155–172. https://www.scopus.com/inward/record.uri?eid=2-s2.0-70849105441&partnerID=40&md5=6c3376cdba582ad347cc2709b5d6195c

Drakos, K. (2002). The Efficiency of the Banking Sector in Central and Eastern Europe. *Russian and East European Finance and Trade*, *38*(2), 31–41. https://www.jstor.org/stable/27749617

Dyckhoff, H. and Allen, K. (2001). Measuring ecological efficiency with data envelopment analysis (DEA). *European Journal of Operational Research*, *132*(2), 312–325. https://doi.org/10.1016/S0377-2217(00)00154-5

Eling, M. and Luhnen, M. (2010). Efficiency in the international insurance industry: A cross-country comparison. *Journal of Banking and Finance*, *34*(7), 1497–1509. https://doi.org/10.1016/j.jbankfin.2009.08.026

Espinosa, C., Maquieira, C., Vieito, J. P. and Gonzalez, M. (2012). Capital Structures in Developing Countries: The Latin American case. *Investigación Económica*, *LXXI*(May), 35–54. http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S0185-16672012000400002&lng=en&tlng=en

Fama, E. F. (1980). Agency Problems and the Theory of the Firm. *Journal of Political Economy*, *88*(2), 288–307. https://doi.org/10.1086/260866

Fama, E. F. and French, K. R. (2002). Testing Trade-Off and Pecking Order Predictions About Dividends and Debt. *Review of Financial Studies*, *15*(1), 1–33. https://doi.org/10.1093/rfs/15.1.1

Färe, R. and Knox Lovell, C. A. (1978). Measuring the technical efficiency of production. *Journal of Economic Theory*, *19*(1), 150–162. https://doi.org/10.1016/0022-0531(78)90060-1

References

Feng, G. and Zhang, X. (2014). Returns to scale at large banks in the US: A random coefficient stochastic frontier approach. *Journal of Banking and Finance*, *39*(1), 135–145. https://doi.org/10.1016/j.jbankfin.2013.10.012

Fernandes, F. D. S., Stasinakis, C. and Bardarova, V. (2018). Two-stage DEA-Truncated Regression: Application in banking efficiency and financial development. *Expert Systems with Applications*, *96*, 284–301. https://doi.org/10.1016/j.eswa.2017.12.010

Fernández, M. A. and Becerra, R. (2013). An Analysis of Spanish Hotel Efficiency. *Cornell Hospitality Quarterly*, *56*(3), 248–257. https://doi.org/10.1177/1938965513509877

Fethi, M. D. and Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. *European Journal of Operational Research*, *204*(2), 189–198. https://doi.org/10.1016/j.ejor.2009.08.003

Fiordelisi, F., Marques-Ibanez, D. and Molyneux, P. (2011). Efficiency and risk in European banking. *Journal of Banking and Finance*, *35*(5), 1315–1326. https://doi.org/10.1016/j.jbankfin.2010.10.005

Fonseka, M. M., Yang, X. and Tian, G. L. (2013). Does accessibility to different sources of financial capital affect competitive advantage and sustained competitive advantages? Evidence from a highly regulated Chinese market. *Journal of Applied Business Research*, *29*(4), 963–982. https://doi.org/10.19030/jabr.v29i4.7908

Forte, D., Barros, L. A. and Nakamura, W. T. (2013). Determinants of the Capital Structure of Small and Medium Sized Brazilian Enterprises. *Brazilian Administration Review*, *10*(3), 347–369. https://doi.org/10.1590/S1807-76922013000300007

Frank, M. Z. and Goyal, V. K. (2003). Testing the pecking order theory of capital structure. *Journal of Financial Economics*, *67*(2), 217–248. https://doi.org/10.1016/S0304-405X(02)00252-0

Fukuyama, H. and Matousek, R. (2011). Efficiency of Turkish banking: Two-stage network system. Variable returns to scale model. *Journal of International Financial Markets, Institutions and Money*, *21*(1), 75–91. https://doi.org/10.1016/j.intfin.2010.08.004

Fukuyama, H. and Matousek, R. (2017). Modelling bank performance: A network DEA approach. *European Journal of Operational Research*, *259*(2), 721–732. https://doi.org/10.1016/j.ejor.2016.10.044

Fukuyama, H. and Weber, W. L. (2008). Japanese banking inefficiency and shadow pricing. *Mathematical and Computer Modelling*, *48*(11–12), 1854–1867. https://doi.org/10.1016/j.mcm.2008.03.004

Fukuyama, H. and Weber, W. L. (2015). Measuring Japanese bank performance: a dynamic network DEA approach. *Journal of Productivity Analysis*, *44*(3), 249–264. https://doi.org/10.1007/s11123-014-0403-1

References

Galán, J. E., Veiga, H. and Wiper, M. P. (2015). Dynamic effects in inefficiency: Evidence from the Colombian banking sector. *European Journal of Operational Research*, *240*(2), 562–571. https://doi.org/10.1016/j.ejor.2014.07.005

Gamba, A. and Triantis, A. (2008). The Value of Financial Flexibility. *The Journal of Finance*, *63*(5), 2263–2296. https://doi.org/10.1111/J.1540-6261.2008.01397.X

Girardone, C., Molyneux, P. and Gardener, E. P. M. (2007). Analysing the determinants of bank efficiency: the case of Italian banks. *Applied Economics*, *36*(3), 215–227. https://doi.org/10.1080/0003684042000175334

Goddard, J., Molyneux, P. and Williams, J. (2014). Dealing with cross-firm heterogeneity in bank efficiency estimates: Some evidence from Latin America. *Journal of Banking and Finance*, *40*(1), 130–142. https://doi.org/10.1016/j.jbankfin.2013.11.025

Goswami, R., Hussain, F. and Kumar, M. (2019). Banking Efficiency Determinants in India: A Two-stage Analysis. *Margin—The Journal of Applied Economic Research*, *13*(4), 361–380. https://doi.org/10.1177/0301574219868373

Graham, J. R. (1996). Debt and the marginal tax rate. *Journal of Financial Economics*, *41*(1), 41–73. https://doi.org/10.1016/0304-405X(95)00857-B

Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, *126*(2), 269–303. https://doi.org/10.1016/j.jeconom.2004.05.003

Greene, W. H. and Segal, D. (2004). Profitability and efficiency in the U.S. life insurance industry. *Journal of Productivity Analysis*, *21*(3), 229–247. https://doi.org/10.1023/B:PROD.0000022092.70204.fa

Gregoire, J. R. and Ramírez Tuya, O. (2006). Cost efficiency of microfinance institutions in Peru: A stochastic frontier approach. *Latin American Business Review*, *7*(2), 41–70. https://doi.org/10.1300/J140v07n02_03

Gregova, E., Smrcka, L., Michalkova, L. and Svabova, L. (2021). Impact of tax benefits and earnings management on capital structures across V4 countries. *Acta Polytechnica Hungarica*, *18*(3), 221–244. https://doi.org/10.12700/APH.18.3.2021.3.12

Guo, H., Legesse, T. S., Tang, J. and Wu, Z. (2021). Financial leverage and firm efficiency: the mediating role of cash holding. *Applied Economics*, *53*(18), 2108–2124. https://doi.org/10.1080/00036846.2020.1855317

Guo, L., Na, S., Tan, X., Gui, P. and Liu, C. (2020). Evolution of the Efficiency of Nationwide Commercial Banks in China Based on an SBM-Undesirable Model and DEA Window Analysis. *Mathematical Problems in Engineering*, *2020*, 1–12. https://doi.org/10.1155/2020/4682790

Gutiérrez, H., Morán, C. and Posas, R. (2018). Determinants of capital structure: An

empirical study of the manufacturing sector at Ecuador. *Contaduria y Administracion*, *64*(2), 1–18. https://doi.org/10.22201/fca.24488410e.2018.1848

Hadri, K. (2000). Testing for stationarity in heterogeneous panel data. *The Econometrics Journal*, *3*(2), 148–161. https://doi.org/10.1111/1368-423X.00043

Halkos, G. E. and Tzeremes, N. G. (2007). Productivity efficiency and firm size: An empirical analysis of foreign owned companies. *International Business Review*, *16*(6), 713–731. https://doi.org/10.1016/j.ibusrev.2007.06.002

Halkos, G. and Petrou, K. N. (2019). Treating undesirable outputs in DEA: A critical review. *Economic Analysis and Policy*, *62*, 97–104. https://doi.org/10.1016/j.eap.2019.01.005

Hanlon, M. and Heitzman, S. (2010). A review of tax research. In *Journal of Accounting and Economics* (Vol. 50, Issues 2–3, pp. 127–178). North-Holland. https://doi.org/10.1016/j.jacceco.2010.09.002

Haron, R. (2014). Firms' speed of adjustment and rational financing behaviour: Malaysian evidence. *Journal for Global Business Advancement*, *7*(2), 151–162. https://doi.org/10.1504/JGBA.2014.063869

Haron, R. and Ibrahim, K. (2013). Dynamic Adjustment towards Target Capital Structure: Thailand Evidence. *Jurnal Pengurusan*, *39*, 73–82. https://doi.org/10.17576/pengurusan-2013-39-07

Havrylchyk, O. (2006). Efficiency of the Polish banking industry: Foreign versus domestic banks. *Journal of Banking and Finance*, *30*(7), 1975–1996. https://doi.org/10.1016/j.jbankfin.2005.07.009

Herring, R. J. and Calomiris, C. W. (2012). Why and How to Design a Contingent Convertible Debt Requirement. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1815406

Higuerey, A., Viñan-Merecí, C., Malo-Montoya, Z. and Martínez-Fernández, V. A. (2020). Data envelopment analysis (DEA) for measuring the efficiency of the hotel industry in Ecuador. *Sustainability (Switzerland)*, *12*(4), 1–18. https://doi.org/10.3390/su12041590

Honma, S. and Hu, J. L. (2012). Analyzing Japanese hotel efficiency. *Tourism and Hospitality Research*, *12*(3), 155–167. https://doi.org/10.1177/1467358412470558

Huang, C. J., Huang, T. H. and Liu, N. H. (2014). A new approach to estimating the metafrontier production function based on a stochastic frontier framework. *Journal of Productivity Analysis*, *42*(3), 241–254. https://doi.org/10.1007/s11123-014-0402-2

Huang, C. W., Chen, H. Y. and Ting, C. Te. (2017). Using a network data envelopment analysis model to assess the efficiency and effectiveness of cultural tourism promotion in Taiwan. *Journal of Travel and Tourism Marketing*, *34*(9), 1274–1284. https://doi.org/10.1080/10548408.2017.1345342

References

Huang, S. and Song, F. (2006). The determinants of capital structure: Evidence from China. *China Economic Review*, *17*(1). https://doi.org/https://doi.org/10.1016/j.chieco.2005.02.007

Huang, T. H., Chiang, D. L. and Chao, S. W. (2017). A new approach to jointly estimating the Lerner index and cost efficiency for multi-output banks under a stochastic meta-frontier framework. *Quarterly Review of Economics and Finance*, *65*, 212–226. https://doi.org/10.1016/j.qref.2016.09.004

Huang, T. H. and Kao, T. L. (2006). Joint estimation of technical efficiency and production risk for multi-output banks under a panel data cost frontier model. *Journal of Productivity Analysis*, *26*(1), 87–102. https://doi.org/10.1007/s11123-006-0007-5

Huhtilainen, M. (2019). Banks' Trust in the EU Macroprudential Regulation. *Journal of Banking and Financial Economics*, *2019*(2), 29–38. https://doi.org/10.7172/2353-6845.jbfe.2019.2.2

Hwang, S.-N. and Chang, T.-Y. (2003). Using data envelopment analysis to measure hotel managerial efficiency change in Taiwan. *Tourism Management*, *31*(3), 357–369. https://doi.org/https://doi.org/10.1016/S0261-5177(02)00112-7

Im, K. S., Pesaran, M. H. and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7

Inui, T., Park, J. and Shin, H.-H. (2008). Internacional comparison of Japanese and Korean Banks.pdf. *Seoul Journal of Economics*, *21*(1). https://www.proquest.com/scholarly-journals/international-comparison-japanese-korean-banking/docview/215574804/se-2

Jarallah, S., Saleh, A. S. A. S. and Salim, R. (2019). Examining pecking order versus trade-off theories of capital structure: New evidence from Japanese firms. *International Journal of Finance and Economics*, *24*(1), 204–211. https://doi.org/10.1002/ijfe.1657

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review*, *72*(6), 323–329. https://doi.org/https://www.jstor.org/stable/1818789

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs, and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/http://dx.doi.org/10.1016/0304-405X(76)90026-X

Jiménez-Hernandez, I., Palazzo, G. and Sáez-Fernández, F. J. (2019). Determinants of bank efficiency: evidence from the Latin American banking industry. *Applied Economic Analysis*, *27*(81), 184–206. https://doi.org/10.1108/AEA-09-2019-0027

Jiménez, G., Lopez, J. A. and Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial Stability*, *9*(2), 185–195. https://doi.org/10.1016/j.jfs.2013.02.004

References

Johnes, J. (2014). Efficiency and Mergers in English Higher Education 1996/97 to 2008/9: Parametric and Non-parametric Estimation of the Multi-input Multi-output Distance Function. *The Manchester School*, *82*(4), 465–487. https://doi.org/10.1111/MANC.12030

Johnson, K. (1981). Towards an Understanding of Labour Turnover. *Service Industries Review*, *1*(1), 4–17. https://doi.org/10.1080/02642068100000002

Jondrow, J., Knox Lovell, C. A., Materov, I. S. and Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, *19*(2–3), 233–238. https://doi.org/10.1016/0304-4076(82)90004-5

Karadag, E. (2010). The road to IFRS convergence in the U.S.: What it may mean for the hospitality industry. *Journal of Hospitality Financial Management*, *18*(1), 45–54. https://doi.org/10.1080/10913211.2010.10653885

Kashyap, A. K. and Stein, J. C. (1994). Monetary policy and bank lending. In *Monetary Policy* (pp. 221–261). The University of Chicago Press. http://www.nber.org/chapters/c8334

Kerman, J. (2011). Neutral noninformative and informative conjugate beta and gamma prior distributions. *Electronic Journal of Statistics*, *5*, 1450–1470. https://doi.org/10.1214/11-EJS648

Kim, H., Kim, J. and Gu, Z. (2012). An examination of US hotel firms' risk features and their determinants of systematic risk. *International Journal of Tourism Research*, *14*(1), 28–39. https://doi.org/10.1002/jtr.828

Kim, S. (2011). Factor determinants of total factor productivity growth in the malaysian hotel industry: A stochastic frontier approach. *Cornell Hospitality Quarterly*, *52*(1), 35–47. https://doi.org/10.1177/1938965509341286

Knox, A. and Nickson, D. (2007). Regulation in Australian hotels: Is there a lesson for the UK? *Employee Relations*, *29*(1), 50–67. https://doi.org/10.1108/01425450710714478

Koop, G. and Steel, M. F. (2001). Bayesian analysis of stochastic frontier models. In *A companion to theoretical econometrics* (pp. 520–537). https://doi.org/10.1002/9780470996249.ch25

Koufodontis, N. I., Zounta, S. and Papagiouvanni, M. (2021). Impact assessment of contemporary international and national accounting standards adoption: evidence from Greek hotels. *Property Management*, *39*(5), 670–685. https://doi.org/10.1108/PM-12-2020-0086

Kraus, A. and Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *The Journal of Finance*, *28*(4), 911–922. https://doi.org/10.1111/j.1540-6261.1973.tb01415.x

References

Kulkarni, P. and Chirputkar, A. V. (2014). Impact of SME Listing on Capital Structure Decisions. *Procedia Economics and Finance*, *11*, 431–444. https://doi.org/10.1016/S2212-5671

Kumar, S., Colombage, S. and Rao, P. (2017). Research on capital structure determinants: a review and future directions. *International Journal of Managerial Finance*, *13*(2), 106–132. https://doi.org/10.1108/IJMF-09-2014-0135

Land, K. C., Lovell, C. A. K. and Thore, S. (1993). Chance-constrained data envelopment analysis. *Managerial and Decision Economics*, *14*(6), 541–554. https://doi.org/10.1002/MDE.4090140607

Lang, G. and Welzel, P. (1999). Mergers Among German Cooperative Banks: A Panel-based Stochastic Frontier Analysis. *Small Business Economics*, *13*(4), 273–286. https://doi.org/10.1023/A:1008130918565

Lang, L., Ofek, E. and Stulz, R. M. (1996). Leverage, investment, and firm growth. *Journal of Financial Economics*, *40*(1), 3–29. https://doi.org/10.1016/0304-405X(95)00842-3

Lee, T. H. and Chih, S. H. (2013). Does financial regulation affect the profit efficiency and risk of banks? Evidence from China's commercial banks. *North American Journal of Economics and Finance*, *26*, 705–724. https://doi.org/10.1016/J.NAJEF.2013.05.005

Leland, H. E. and Pyle, D. H. (1977). Informational Asymmetries, Financial Structure, and Financial Intermediation. *The Journal of Finance*, *32*(2), 371. https://doi.org/10.2307/2326770

Lemma, T. T. and Negash, M. (2014). Determinants of the adjustment speed of capital structure: Evidence from developing economies. *Journal of Applied Accounting Research*, *15*(1), 64–99. https://doi.org/10.1108/JAAR-03-2012-0023

Letti, A. G., Bittencourt, M. V. L. and Vila, L. E. (2022). Stochastic vs. deterministic frontier distance output function: Evidence from Brazilian higher education institutions. *Journal of Productivity Analysis*, *58*(1), 55–74. https://doi.org/10.1007/s11123-022-00636-1

Levin, A., Lin, C. F. and Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, *108*(1), 1–24. https://doi.org/10.1016/S0304-4076(01)00098-7

Li, H. and Cui, L. (2003). Empirical Study of Capital Structure on Agency Costs in Chinese Listed Firms. *Nature and Science*, *1*(1), 12–20. https://doi.org/10.4324/9780203698693

Li, H. and Stathis, P. (2017). Determinants of capital structure in Australia: an analysis of important factors. *Managerial Finance*, *43*(8), 881–897. https://doi.org/10.1108/MF-02-2017-0030

Li, L. and Islam, S. (2019). Firm and industry specific determinants of capital structure: Evidence from the Australian market. *International Review of Economics and Finance*,

59, 425–437. https://doi.org/10.1016/j.iref.2018.10.007

López-Gracia, J. and Sogorb-Mira, F. (2008). Testing trade-off and pecking order theories financing SMEs. *Small Business Economics*, *31*(2), 117–136. https://doi.org/10.1007/s11187-007-9088-4

M'ng, J. C. P., Rahman, M. and Sannacy, S. (2017). The determinants of capital structure: Evidence from public listed companies in Malaysia, Singapore and Thailand. *Cogent Economics and Finance*, *5*(1), 1–34. https://doi.org/10.1080/23322039.2017.1418609

Maddala, G. S. and Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, *61*(SUPPL.), 631–652. https://doi.org/10.1111/1468-0084.0610S1631

Manlagñit, M. C. V. (2011). Cost efficiency, determinants, and risk preferences in banking: A case of stochastic frontier analysis in the Philippines. *Journal of Asian Economics*, *22*(1), 23–35. https://doi.org/10.1016/j.asieco.2010.10.001

Martinez, L. B., Scherger, V. and Guercio, M. B. (2019). SMEs capital structure: trade-off or pecking order theory: a systematic review. *Journal of Small Business and Enterprise Development*, *26*(1), 105–132. https://doi.org/10.1108/JSBED-12-2017-0387

Matthews, K. (2013). Risk management and managerial efficiency in Chinese banks: A network DEA framework. *Omega (United Kingdom)*, *41*(2), 207–215. https://doi.org/10.1016/j.omega.2012.06.003

Meslier, C., Tacneng, R. and Tarazi, A. (2014). Is bank income diversification beneficial? Evidence from an emerging economy. *Journal of International Financial Markets, Institutions and Money*, *31*(1), 97–126. https://doi.org/10.1016/j.intfin.2014.03.007

Mester, L. J. (1996). A study of bank efficiency taking into account risk-preferences. *Journal of Banking and Finance*, *20*(6), 1025–1045. https://doi.org/10.1016/0378-4266(95)00047-X

Michaelas, N., Chittenden, F. and Poutziouris, P. (1999). Financial Policy and Capital Structure Choice in U.K. SMEs: Empirical Evidence from Company Panel Data. *Small Business Economics*, *12*(2), 113–130. https://doi.org/10.1023/A:1008010724051

Miller, M. H. (1977). Debt and Taxes. *The Journal of Finance*, *32*(2), 261. https://doi.org/10.2307/2326758

Minh, N. K., Long, G. T. and Hung, N. V. (2013). Efficiency and super-efficiency of commercial banks in Vietnam: Performances and determinants. *Asia-Pacific Journal of Operational Research*, *30*(1). https://doi.org/10.1142/S0217595912500479

Modigliani, F. and Miller, M. H. (1958). The cost of Captial, corporate finance and investment.pdf. In *American Economic Review.* (Vol. 48, Issue 3, pp. 261–297). https://www.jstor.org/stable/1809766

References

Modigliani, F. and Miller, M. H. (1963). Corporate Income Taxes and the Cost of Capital: A Correction. *American Economic Review*, *53*(3), 433–443. https://doi.org/https://www.jstor.org/stable/1809167

Montalván, J. (2019). Determinants of the Capital Structure: An Analysis of Ecuadorian SMEs with Financing in the Stock Market. *X-Pedientes Económicos*, *3*(7), 57–75.

Morey, R. C. and Dittman, D. A. (1995). Evaluating a Hotel GM's Performance A Case Study in Benchmarking. *Cornell Hotel and Restaurant Administration Quarterly*, *36*(5), 30–35. https://doi.org/10.1177/001088040304400507

Mutuku, M. K., Muathe, S. and James, R. (2019). Mediating Effect of Competitive Advantage on the Relationship Between E-commerce Capability and Performance: Empirical Evidence from Commercial Banks in Kenya. *European Journal of Business and Management*, *11*(17), 48–57. https://doi.org/10.7176/EJBM

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, *5*(2), 147–175. https://doi.org/10.1016/0304-405X(77)90015-0

Myers, S. C. (1984). Finance Theory and Financial Strategy. *Interfaces*, *14*(1), 126–137. https://doi.org/10.1287/inte.14.1.126

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*(2), 187–221. https://doi.org/10.1016/0304-405X(84)90023-0

Ng, S. (2008). A simple test for nonstationarity in mixed panels. *Journal of Business and Economic Statistics*, *26*(1), 113–127. https://doi.org/10.1198/073500106000000675

Nguyen, T. L. A. (2018). Diversification and bank efficiency in six ASEAN countries. *Global Finance Journal*, *37*, 57–78. https://doi.org/10.1016/J.GFJ.2018.04.004

O'Donnell, C. J. and Coelli, T. J. (2005). A Bayesian approach to imposing curvature on distance functions. *Journal of Econometrics*, *126*(2), 493–523. https://doi.org/10.1016/j.jeconom.2004.05.011

O'Donnell, C. J., Rao, D. S. P. and Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics*, *34*(2), 231–255. https://doi.org/10.1007/s00181-007-0119-4

Öhman, P. and Yazdanfar, D. (2017). Short- and long-term debt determinants in Swedish SMEs. *Review of Accounting and Finance*, *16*(1), 102–118. https://doi.org/10.1108/RAF-08-2015-0118

Oleas-Montalvo, J. (2020). ECUADOR: LA ECONOMÍA POLÍTICA DEL FERIADO BANCARIO (8-12 DE MARZO DE 1999). *Revista Uruguaya De Historia Economica*, *17*(17), 49–67. https://doi.org/10.47003/ruhe/10.17.03

References

Oliveira, G. R., Tabak, B. M., de Lara Resende, J. G. and Cajueiro, D. O. (2013). Determinants of the level of indebtedness for Brazilian firms: A quantile regression approach. *EconomiA*, *14*(3–4), 123–138. https://doi.org/10.1016/j.econ.2013.11.002

Orbe León, J. and Caria, S. (2019). La economía ecuatoriana en la encrucijada: balance de una década polémica, 2007-2017. In *Economía y sociedad* (Vol. 1). Instituto de Altos Estudios Nacionales. https://editorial.iaen.edu.ec/presentacion-la-economia-ecuatoriana-en-la-encrucijada-balance-de-una-decada-polemica-2007-2017/

Osuagwu, E. S., Isola, W. A. and Nwaogwugwu, I. C. (2018). Measuring technical efficiency and productivity change in the nigerian banking sector: A comparison of non-parametric and parametric techniques. *African Development Review*, *30*(4), 490–501. https://doi.org/10.1111/1467-8268.12357

Oukil, A., Channouf, N. and Al-Zaidi, A. (2016). Performance evaluation of the hotel industry in an emerging tourism destination: The case of Oman. *Journal of Hospitality and Tourism Management*, *29*, 60–68. https://doi.org/10.1016/j.jhtm.2016.05.003

Palacín-Sánchez, M. J., Ramírez-Herrera, L. M. and di Pietro, F. (2013). Capital structure of SMEs in Spanish regions. *Small Business Economics*, *41*(2), 503–519. https://doi.org/10.1007/s11187-012-9439-7

Panno, A. (2003). An empirical investigation on the determinants of capital structure: The UK and Italian experience. *Applied Financial Economics*, *13*(2), 97–112. https://doi.org/10.1080/09603100210100882

Paradi, J. C., Rouatt, S. and Zhu, H. (2011). Two-stage evaluation of bank branch efficiency using data envelopment analysis. *Omega*, *39*(1), 99–109. https://doi.org/10.1016/j.omega.2010.04.002

Paredes Gómez, A., Ángeles Castro, G. and Flores Ortega, M. (2016). Determinants of leverage in mining companies, empirical evidence for Latin American countries. *Contaduria y Administracion*, *61*(1), 26–40. https://doi.org/10.1016/j.cya.2015.09.010

Park, K. H. and Weber, W. L. (2006). A note on efficiency and productivity growth in the Korean Banking Industry, 1992-2002. *Journal of Banking and Finance*, *30*(8), 2371–2386. https://doi.org/10.1016/j.jbankfin.2005.09.013

Parte-Esteban, L. and Alberca-Oliver, P. (2015). Determinants of technical efficiency in the Spanish hotel industry: regional and corporate performance factors. *Current Issues in Tourism*, *18*(4), 391–411. https://doi.org/10.1080/13683500.2013.800029

Partovi, E. and Matousek, R. (2019). Bank efficiency and non-performing loans: Evidence from Turkey. *Research in International Business and Finance*, *48*, 287–309. https://doi.org/10.1016/j.ribaf.2018.12.011

Pastor, J. T., Ruiz, J. L. and Sirvent, I. (1999). An Enhanced DEA Russell graph efficiency measure. *European Journal of Operational Research*, *115*(3), 596–607.

https://doi.org/10.1016/S0377-2217(98)00098-8

Patiño, L. M. (2001). Lessons from the financial crisis in Ecuador in 1999. *Journal of International Banking Regulation*, *3*(1), 37–70.

Perera, S., Skully, M. and Wicramanayake, J. (2008). Cost Efficiency in South Asian Banking: The Impact of Bank Size, State Ownership and Stock Exchange Listings*. *International Review of Finance*, *7*(1–2), 35–60. https://doi.org/10.1111/j.1468-2443.2007.00067.x

Pérez-Rodríguez, J. V. and Acosta-González, E. (2023). The impact of ownership and size heterogeneity on hotel efficiency in the Canary Islands (Spain). *Tourism Economics*, *29*(3), 1–27. https://doi.org/10.1177/13548166211035853

Pesaran, M. H. (2012). On the interpretation of panel unit root tests. *Economics Letters*, *116*(3), 545–546. https://doi.org/10.1016/J.ECONLET.2012.04.049

Pessarossi, P. and Weill, L. (2015). Do capital requirements affect cost efficiency? Evidence from China. *Journal of Financial Stability*, *19*, 119–127. https://doi.org/10.1016/j.jfs.2014.11.002

Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal*, *14*(3), 179–191. https://doi.org/10.1002/smj.4250140303

Pointer, L. V and Khoi, P. D. (2019). Predictors of return on assets and return on equity for banking and insurance companies on Vietnam stock exchange. *Entrepreneurial Business and Economics Review*, *7*(4), 185–198. https://doi.org/10.15678/EBER.2019.070411

Porter, M. (1980). *Competitive Strategy*. The Fee Press.

Proaño-Rivera, B. and Feria-Dominguez, J. M. (2023). Are Ecuadorian banks enough technically efficient for growth? A clinical study. *International Journal of Finance and Economics*, *December 2022*. https://doi.org/10.1002/ijfe.2775

Proença, C., Augusto, M. and Murteira, J. (2023). The effect of earnings management on bank efficiency: Evidence from ECB-supervised banks. *Finance Research Letters*, *51*(August 2022). https://doi.org/10.1016/j.frl.2022.103450

Quispe-Agnoli, M. and Whisler, E. (1998). Official Dollarization and the Banking System in Ecuador and El Salvador. *Economic Review-Federal Reserve Bank of Atlanta, 91(3), 55*, *91*(3), 55–71.

Rajan, R. and Zingales, L. (1995). What Do We Know about Capital Structure? Some Evidence from International Data. *The Journal of Finance*, *50*(5), 1421–1460. https://doi.org/10.1111/j.1540-6261.1995.tb05184.x

References

Ramjee, A. and Gwatidzo, T. (2012). Dynamics in capital structure determinants in South Africa. *Meditari Accountancy Research*, *20*(1), 52–67. https://doi.org/10.1108/10222521211234228

Rani, N., Yadav, S. S. and Tripathy, N. (2019). Capital structure dynamics of Indian corporates. *Journal of Advances in Management Research*, *17*(2), 212–225. https://doi.org/10.1108/JAMR-12-2017-0125

Řepková, I. (2015). Banking Efficiency Determinants in the Czech Banking Sector. *Procedia Economics and Finance*, *23*, 191–196. https://doi.org/10.1016/s2212-5671(15)00367-6

Reynolds, D. and Thompson, G. M. (2007). Multiunit restaurant productivity assessment using three-phase data envelopment analysis. *International Journal of Hospitality Management*, *26*(1), 20–32. https://doi.org/10.1016/J.IJHM.2005.08.004

Ritter, J. R. (2003). Behavioral finance. *Pacific Basin Finance Journal*, *11*(4), 429–437. https://doi.org/10.1016/S0927-538X(03)00048-9

Rivera Godoy, J. A. (2007). Estructura financiera y factores determinantes de la estructura de capital de las pymes del sector de confecciones. *Cuadernos de Administración*, *20*(34), 191–219. http://www.redalyc.org/html/205/20503409/

Robichek, A. A. and Myers, S. C. (1966). Problems in the Theory of Optimal Capital Structure. *The Journal of Financial and Quantitative Analysis*, *1*(2), 1–35. https://doi.org/10.2307/2329989

Rodrigues, S. V., de Moura, H. J., Santos, D. F. L. and Sobreiro, V. A. (2017). Capital structure management differences in Latin American and US firms after 2008 crisis. *Journal of Economics, Finance and Administrative Science*, *22*(42), 51–74. https://doi.org/10.1108/JEFAS-01-2017-0008

Rodríguez-Victoria, O. E., Puig, F. and González-Loureiro, M. (2017). Clustering, innovation and hotel competitiveness: evidence from the Colombia destination. *International Journal of Contemporary Hospitality Management*, *29*(11), 2785–2806. https://doi.org/10.1108/IJCHM-03-2016-0172

Romero-Galarza, A., Flores-Sánchez, G., Reyes-Zambrano, B. and Campoverde-Campoverde, J. (2020). Evaluation of the concentration and competition of ecuadorian banking sector in 2006- 2018 period. *Boletín de Coyuntura*, *24*, 4–12. https://doi.org/10.31243/bcoyu.24.2020.882

Ross, S. A. (1977). Determination of financial structure: The incentive-signalling approach. *Bell Journal of Economics*, *8*(1), 23–40. https://doi.org/10.2307/3003485

Sadalia, I., Haikal Kautsar, M., Irawati, N. and Muda, I. (2018). Analysis of the efficiency performance of Sharia and conventional banks using stochastic frontier analysis. *Banks and Bank Systems*, *13*(2), 27–38. https://doi.org/10.21511/bbs.13(2).2018.03

References

Sari, P. Z. and Saraswati, E. (2017). The Determinant of Banking Efficiency in Indonesia (DEA Approach). *Journal of Accounting and Business Education*, *1*(2), 208. https://doi.org/10.26675/jabe.v1i2.8489

Sarmiento, G. (2017). Fiscalidad y estructura de capital de las empresas manufactureras ecuatorianas, en el periodo 2012 – 2015. *Revista Publicando*, *4*(13), 294–314.

Sarmiento, M. and Galán, J. E. (2018). Heterogeneous Effects of Risk-Taking on Bank Efficiency: A Stochastic Frontier Model with Random Coefficients. *SSRN Electronic Journal*, Article 14–20. https://doi.org/10.2139/ssrn.2477115

Serrasqueiro, Z., Macas, P. aulo and Nunes, P. M. (2012). Is Age a Determinant of SMEs' Financing Decisions? Empirical Evidence Using Panel Data Models. *Entrepreneurship: Theory and Practice*, *36*(4), 627–654. https://doi.org/10.1111/j.1540-6520.2010.00433.x

Shang, J. K., Wang, F. C. and Hung, W. T. (2010). A stochastic DEA study of hotel efficiency. *Applied Economics*, *42*(19), 2505–2518. https://doi.org/10.1080/00036840701858091

Shanmugam, K. R. and Das, A. (2004). Efficiency of Indian commercial banks during the reform period. *Applied Financial Economics*, *14*(9), 681–686. https://doi.org/10.1080/0960310042000233458

Shi, X., Emrouznejad, A. and Yu, W. (2021). Overall efficiency of operational process with undesirable outputs containing both series and parallel processes: A SBM network DEA model. *Expert Systems with Applications*, *178*, 115062. https://doi.org/10.1016/j.eswa.2021.115062

Shyam-Sunder, L. and Myers, S. C. (1999). Testing static tradeoff against pecking order models of capital structure. *Journal of Financial Economics*, *51*(2), 219–244. https://doi.org/10.1016/s0304-405x(98)00051-8

Silva, M., Gomes, L. P. and Lopes, I. C. (2020). Explanatory factors of the capital structure. *Emerging Science Journal*, *4*(6), 519–529. https://doi.org/10.28991/esj-2020-01249

Silva Serrasqueiro, Z., Armada, M. R. and Nunes, P. M. (2011). Pecking Order Theory versus Trade-Off Theory: Are service SMEs' capital structure decisions different? *Service Business*, *5*(4), 381–409. https://doi.org/10.1007/s11628-011-0119-5

Silva Serrasqueiro, Z. M. and Rêgo Rogão, M. C. (2009). Capital structure of listed Portuguese companies: Determinants of debt adjustment. *Review of Accounting and Finance*, *8*(1), 54–75. https://doi.org/10.1108/14757700910934238

Simar, L. and Wilson, P. W. (1998). Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Management Science*, *44*(1), 49–61. https://doi.org/10.1287/MNSC.44.1.49

References

Simar, L. and Wilson, P. W. (2000). A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics*, *27*(6), 779–802. https://doi.org/10.1080/02664760050081951

Simar, L. and Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31–64. https://doi.org/10.1016/J.JECONOM.2005.07.009

Singh, P. K. and Thaker, K. (2020). Profit efficiency and determinants of Indian banks; A truncated bootstrap and data envelopment analysis. *Cogent Economics and Finance*, *8*(1). https://doi.org/10.1080/23322039.2020.1724242

Skalpe, O. (2003). Hotels and restaurants - Are the risks rewarded? Evidence from Norway. *Tourism Management*, *24*(6), 623–634. https://doi.org/10.1016/S0261-5177(03)00045-1

Spiegelhalter, D. J., Best, N. G., Carlin, B. P. and van der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, *64*(4), 583–616. https://doi.org/10.1111/1467-9868.00353

Spulbăr, C. and Niţoi, M. (2014). Determinants of bank cost efficiency in transition economies: Evidence for Latin America, Central and Eastern Europe and South-East Asia. *Applied Economics*, *46*(16), 1940–1952. https://doi.org/10.1080/00036846.2014.889806

Stewart, C., Matousek, R. and Nguyen, T. N. (2016). Efficiency in the Vietnamese banking system: A DEA double bootstrap approach. In *Research in International Business and Finance* (Vol. 36, pp. 96–111). https://doi.org/10.1016/j.ribaf.2015.09.006

Stiglitz, J. E. (1969). A Re-examination of Modigliani and Miller.pdf. *The American Economic Review*, *59*(5), 784–793. https://www.jstor.org/stable/1810676

Stiglitz, J. E. and Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *The American Economic Review*, *71*(3), 393–410. http://www.jstor.org/stable/1802787

Stradomski, M. and Schmidt, K. (2020). Firm specific determinants of capital structure in European advanced developing countries | Mikrodeterminanty struktury kapitału przedsiębiorstw z europejskich zaawansowanie rozwijających się gospodarek. *Bank i Kredyt*, *53*(3), 263–292.

Stulz, R. M. (1990). Managerial discretion and optimal financing policies. *Journal of Financial Economics*, *26*(1), 3–27. https://doi.org/10.1016/0304-405X(90)90011-N

Sufian, F. (2015). Determinants of Malaysian bank efficiency: evidence from bootstrap data envelopment analysis. *International Journal of Applied Nonlinear Science*, *2*(1/2), 100. https://doi.org/10.1504/ijans.2015.076529

Sun, S., Lu, W.-M. and Wen-Min, L. U. (2005). Evaluating the performance of the Taiwanese

hotel industry using a weight slacks-based measure. *Asia-Pacific Journal of Operational Research*, *22*(4), 487–512. https://doi.org/10.1142/S0217595905000595

Tabak, B. M., Fazio, D. M. and Cajueiro, D. O. (2012). The relationship between banking market competition and risk-taking: Do size and capitalization matter? *Journal of Banking and Finance*, *36*(12), 3366–3381. https://doi.org/10.1016/j.jbankfin.2012.07.022

Tahir, I. M. and Haron, S. (2008). Technical efficiency of the Malaysian commercial banks: A stochastic frontier approach. *Banks and Bank Systems*, *3*(4), 65–72. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84857003035&partnerID=40&md5=b2312174051ec031614ae91e42e934d8

Tamule, H. B., Bubnys, E. L. and Sugrue, T. F. (1993). Dividend reinvestment plans and Pecking Order capital structure behavior: An empirical investigation. *Journal of Economics and Finance*, *17*(1), 91–101. https://doi.org/10.1007/BF02920085

Tan, Y. and Despotis, D. (2021). Investigation of efficiency in the UK hotel industry: a network data envelopment analysis approach. *International Journal of Contemporary Hospitality Management*, *33*(3), 1080–1104. https://doi.org/10.1108/IJCHM-07-2020-0641

Tawiah, V. and Boolaky, P. (2020). Consequences and determinants of IFRS convergence in India. *International Journal of Accounting and Information Management*, *28*(2), 303–322. https://doi.org/10.1108/IJAIM-06-2019-0062

Tecles, P. L. and Tabak, B. M. (2010). Determinants of bank efficiency: The case of Brazil. *European Journal of Operational Research*, *207*(3), 1587–1598. https://doi.org/10.1016/j.ejor.2010.06.007

Titman, S. and Wessels, R. (1988). The Determinants of Capital Structure Choice. *The Journal of Finance*, *43*(1), 1–19. https://doi.org/10.1111/j.1540-6261.1988.tb02585.x

Tone, K. (2001). Slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, *130*(3), 498–509. https://doi.org/10.1016/S0377-2217(99)00407-5

Tone, K. (2003). *Dealing with undesirable outputs in DEA: A Slacks-Based Measure (SBM) approach*. GRIPS Research Report Series I-2003-0005.

Torres Cumbicus, G. (2020). *20 años de dolarización de la economía ecuatoriana: Análisis del sector monetarios y financiero*. Banco Central de Ecuador. https://www.bce.fin.ec/micrositio20dolarizacion/sector-monetario-financiero.html

Tristão, P. A. and Sonza, I. B. (2019). Is the capital structure stable in Brazil? | A estrutura de capital no Brasil é estável? *Revista de Administracao Mackenzie*, *20*(4), 1–29. https://doi.org/10.1590/1678-6971/eRAMF190154

References

Tsionas, E. G. (2002). Stochastic frontier models with random coefficients. *Journal of Applied Econometrics*, *17*(2), 127–147. https://doi.org/10.1002/JAE.637

Tsionas, E. G., Kumbhakar, S. C. and Malikov, E. (2015). Estimation of Input Distance Functions: A System Approach. *American Journal of Agricultural Economics*, *97*(5), 1478–1493. https://doi.org/10.1093/AJAE/AAV012

Tzeremes, N. G. (2019). Hotel productivity: A robust Luenberger productivity indicator. *Tourism Economics*, *25*(6), 987–996. https://doi.org/10.1177/1354816618821271

Tzeremes, N. G. (2021). Robust malmquist productivity measurement: evidence from Spanish hotel industry during the Great Recession. *International Journal of Productivity and Performance Management*, *70*(2), 408–426. https://doi.org/10.1108/IJPPM-01-2019-0037/FULL/XML

Unda, L. A. and Margret, J. (2015). Transformation of the Ecuadorian financial system: regulation and response. *Journal of Financial Regulation and Compliance*, *23*(1), 84–102. https://doi.org/10.1108/JFRC-02-2014-0016

Uzcátegui-Sánchez, C., Camino-Mogro, S. and Moran-Cruz, J. C. (2018). Estructura de mercado del sistema bancario ecuatoriano: concentración y poder de mercado. *Cumbres*, *4*(1), 49–62. https://doi.org/10.48190/cumbres.v4n1a5

Vasiliou, D., Eriotis, N. and Daskalakis, N. (2009). Testing the pecking order theory: the importance of methodology. *Qualitative Research in Financial Markets*, *1*(2), 85–96. https://doi.org/10.1108/17554170910975900

Vera-Gilces, P., Camino-Mogro, S., Ordeñana-Rodríguez, X. and Cornejo-Marcos, G. (2020). A look inside banking profitability: Evidence from a dollarized emerging country. *The Quarterly Review of Economics and Finance*, *75*(2020), 147–166. https://doi.org/10.1016/j.qref.2019.05.002

Vernikov, A. and Mamonov, M. (2018). Modelling technical efficiency of firms under one-step and two-step approaches (the case of commercial banks). *Applied Econometrics*, *49*, 67–90. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85053337311&partnerID=40&md5=159ae6f2460f7159bfd20201fd3d7ac0

Vivel-Búa, M., Lado-Sestayo, R. and Otero-González, L. (2018). Risk determinants in the hotel sector: Risk credit in MSMEs. *International Journal of Hospitality Management*, *70*, 110–119. https://doi.org/10.1016/j.ijhm.2017.11.004

Vollmer, U. and Wiese, H. (2013). Minimum capital requirements, bank supervision and special resolution schemes. Consequences for bank risk-taking. *Journal of Financial Stability*, *9*(4), 487–497. https://doi.org/10.1016/j.jfs.2013.07.004

Wald, J. K. (1999). How firm characteristics affect capital structure: An international comparison. *Journal of Financial Research*, *22*(2), 161–187. https://doi.org/10.1111/j.1475-6803.1999.tb00721.x

References

Walsh, E. J. and Ryan, J. (1997). Agency and Tax Explanations of Security Issuance Decisions. *Journal of Business Finance & Accounting*, *24*(7&8), 943–961. https://doi.org/10.1111/1468-5957.00144

Wang, F. C., Hung, W. T. and Shang, J. K. (2006). Measuring the cost efficiency of international tourist hotels in Taiwan. *Tourism Economics*, *12*(1), 65–85. https://doi.org/10.5367/000000006776387150

Wang, Y., Wen, Z., Cao, X., Zheng, Z. and Xu, J. (2020). Environmental efficiency evaluation of China's iron and steel industry: A process-level data envelopment analysis. *Science of the Total Environment*, *707*, 135903. https://doi.org/10.1016/j.scitotenv.2019.135903

Warner, J. B. (1977). Bankruptcy, absolute priority, and the pricing of risky debt claims. *Journal of Financial Economics*, *4*(3), 239–276. https://doi.org/10.1016/0304-405X(77)90002-2

Weisbrot, M., Johnston, J. and Lefebvre, S. (2013). Ecuador's New Deal: Reforming and Regulating the Financial Sector. In *CEPR Reports and Issue Briefs* (Issue February). www.cepr.net

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171–180. https://doi.org/10.1002/smj.4250050207

Wu, L. (2011). The Impact of Ownership Structure on Debt Financing of Japanese Firms With the Agency Cost of Free Cash Flow. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.488042

Yazdanfar, D. and Ödlund, L. (2010). Industry effects and micro firms' capital structure determinants empirical evidence from Swedish data. *International Journal of Business and Globalisation*, *5*(4), 373–387. https://doi.org/10.1504/IJBG.2010.035473

Yeyati, E. L. and Micco, A. (2007). Concentration and foreign penetration in Latin American banking sectors: Impact on competition and risk. *Journal of Banking and Finance*, *31*(6), 1633–1647. https://doi.org/10.1016/j.jbankfin.2006.11.003

Yildirim, H. S., Akci, Y. and Eksi, I. H. (2013). The effect of firm characteristics in accessing credit for SMEs. *Journal of Financial Services Marketing*, *18*(1), 40–52. https://doi.org/10.1057/fsm.2012.28

Yu, D. D. and Aquino, R. Q. (2009). Testing capital structure models on philippine listed firms. *Applied Economics*, *41*(15), 1973–1990. https://doi.org/10.1080/00036840601131805

Zhang, D., Tu, J., Zhou, L. and Yu, Z. (2020). Higher tourism specialization, better hotel industry efficiency? *International Journal of Hospitality Management*, *87*, 102509. https://doi.org/10.1016/j.ijhm.2020.102509

Appendix

Table A1. Empirical studies on capital structure around the world.

Authors, Year	Country	Data set, Period analysed	Econometric methods	Conclusions/findings
***PANEL A*: Developed countries**				
Bradley et al. (1984)	United States	851 listed companies (1962-1981)	ANOVA, Ordinary least squares	Leverage is inversely related to bankruptcy costs and the non-debt tax shield. If bankruptcy costs are significant, corporate earnings volatility is a significant inverse determinant of leverage.
Titman and Wessles (1988)	United States	469 manufacturing listed firms (1974-1982)	Factor-analytic (LISREL)	Leverage is negatively related to the uniqueness of the business line and past profitability. Short-term debt is negatively related to size. Other variables such as volatility, collateral value, non-debt tax shield or growth opportunities did not affect leverage.
Chung (1993)	United States	1130 non-regulated-sector firms, 319 regulated-sector firms (1980-1984)	Ordinary least squares	Companies with greater asset diversification and a higher percentage of fixed assets tend to use more long-term debt. Firms with significant growth opportunities and considerable operational risk tend to use less short-term and long-term debt. Companies in regulated sectors use more long-term debt.
Chittenden et al. (1996)	United Kingdom	172 listed and 3308 non-listed small companies (1993-1997)	Ordinary least squares	Profitability and asset structure are strongly and negatively related to short-term leverage. In addition, access to the capital market itself seems to be an essential factor determining small firms' capital structure. The determinants with long-term leverage tend to be weak in non-listed firms and stronger in listed firms.
Frank and Goyal (2003)	United States	768 listed firms (1971-1998)	Fixed effects	The coefficient of lagged leverage is strongly significant and negative, as expected by trade-off theory. The incorporation of lagged leverage as an explanatory variable does not affect the significance of other variables.
Panno (2003)	United Kingdom and Italy	87 UK listed firms, 63 Italian firms (1992-1996)	Logit and probit	The results imply that companies in developed markets (UK) tend to have long-term debt targets; however, other variables seem more important than the search for optimal leverage ratios in less efficient markets (Italy).
Cassar and Holmes (2003)	Australia	1555 SMEs	Ordinary least squares	The results generally corroborate the arguments of the Trade-off and Pecking-order theories. Determinants such as profitability, growth and asset structure are significantly related to leverage.
Aivazian et al. (2005)	Canada	863 listed firms (1982- 1999)	Pooled regression, random effects, and fixed effects	Leverage is indirectly related to investment; this effect is more significant in companies with low growth opportunities than in high growth ones.

Appendix

Sánchez-Vidal and Martín-Ugedo (2005)	Spain	1566 non-financial companies (1994-2000)	Fixed effects	The results corroborate the Pecking-order theory in small and medium-sized companies and in those with high leverage and growth.
Silva Serrasqueiro and Rêgo Rogão (2009)	Portugal	41 listed non-financial companies (1991-2004)	Ordinary least squares	Transaction costs are relevant to debt issuance. Tangibility and size are determinants that affect the adjustment of debt towards the optimal level. Capital structure decisions can be explained under the Trade-off and Pecking-order theories.
Serrasqueiro et al. (2012)	Portugal	495 young firms, 1350 older firms (1999-2006)	Probit regression, Generalised method of moments	Age is a determining factor in the financing decisions of SMEs. Furthermore, the results imply that both the Pecking-order and the Trade-off theories are necessary to explain capital structure decisions.
Li and Islam (2019)	Australia	1709 listed companies (1999- 2012)	Ordinary least squares	According to the significant results, the Pecking-order theory dominates: profitability and leverage present a negative relationship, while size and growth opportunities influence the leverage positively and negatively, respectively. Results vary among industries.
Jarallah et al. (2019)	Japan	1,362 publicly listed nonfinancial firms (1991-2015)	Generalised method of moments, Fixed effects	The results demonstrate that the Pecking-order theory supports the financing behaviour of listed Japanese firms, while the debt maturity structure conforms to the Trade-off theory.
Silva et al. (2020)	Portugal	55 listed firms (2014-2016)	Random effects	Pecking-order and Trade-off theories partially explain leverage decisions. Leverage is directly related to tangibility and size and indirectly related to cash flows.
Gregova et al. (2021)	Czech Republic, Hungary, Poland and Slovakia	10627 listed or non-listed companies (2014-2017)	Jones model (modified), Fixed effects	The results are more coherent with the Pecking-order theory. In all four countries, profitability, taxes and liquidity negatively affect leverage, while growth and tangibility (except in Hungary) have a positive impact; in Hungary and the Czech Republic, size negatively affects leverage, while in Poland and Slovakia, the effect is positive. Debt monitoring decreases agency costs by reducing the application of earnings management techniques.
de Jong et al. (2011)	United States	2259 non-financial listed firms (1985-2005)	Generalised method of moments, Fixed effects	The Pecking-order theory better describes decisions to issue securities than the Trade-off theory. By contrast, the Trade-off theory is a stronger predictor of firms' leverage decisions regarding securities repurchases.
Palacín-Sánchez et al. (2013)	Spain	13,838 SMEs (2004–2007)	Generalised least squares	The capital structure differs by region. The effect of the determinants of leverage differs in signs, significance and magnitude.
Adair and Adaskou (2015)	France	2370 SMEs (2002-2010)	Ordinary least squares, Fixed effects, Random effects	Following the Trade-off theory, trade credit signals to borrowers with little private information about the firm, and access to the loan depends on collateral. The relationship between leverage and profitability, as well as growth opportunities, support the Trade-off theory.
Li and Stathis (2017)	Australia	368 listed companies (1984-2007)	Fixed effects	Profitability is indirectly related to leverage, in accordance with the Pecking-order theory. However, when taxes increase, the Trade-off theory becomes relevant.
Öhman and Yazdanfar (2017)	Switzerland	5897 SMEs (2009-2012)	Ordinary least squares, Fixed effects	Short-term debt is directly related to size and growth and indirectly related to profitability, liquidity, age and tangibility. Long-term debt is directly related to growth and tangibility and indirectly related to profitability, size, non-debt tax shields and liquidity. The Pecking-order theory is predominant.
***PANEL B*: Developing countries**				
Huang and Song (2002)	China	1000 listed firms	Ordinary least squares	The ownership structure influences leverage. In addition, leverage rises with variability, and companies then reduce their long-term debt. Leverage ratios decrease with profitability and increase with firm size. The Trade-off theory seems to explain leverage more accurately than the Pecking-order theory.

Appendix

Li and Cui, (2003)	China	211 non-financial listed firms	Ordinary least squares	Firms with a higher debt ratio have greater asset efficiency and returns on equity, and this relationship is statistically significant. Therefore, the results obtained are closer to the Trade-off theory than to the Pecking-order theory.
Dragotă et al. (2008)	Romania	60 non-financial listed companies (1997-2005)	Granger causality	Tangibility, size, profitability and market-to-book ratios are significant determinants of capital structure.
Yu and Aquino (2009)	Philippines	150 listed firms (1990- 2001)	Fixed effects	Leverage ratios tend towards their optimal level, which supports the Trade-off theory. Nevertheless, profitability and capital structure are indirectly related, which supports the Pecking order theory.
Chakraborty (2010)	India	1169 non-financial listed firms (1995–2008)	Ordinary least square and Generalised method of moments	Pecking-order and Trade-off theories seem to explain the decisions of Indian firms. Size, profitability and uniqueness are negatively related to leverage, while non-debt tax shields and tangibility are positively associated with leverage.
Ahmed Sheikh and Wang (2011)	Pakistan	160 listed manufacturing companies (2003-2007)	Ordinary least squares, Random effects, and Fixed effects	Leverage is negatively affected by liquidity, profitability, earnings volatility and tangibility, while size is positively related to debt. Growth opportunities and non-debt tax shields are not significantly related to leverage. The results are consistent with the Pecking-order predictions and with Trade-off theory.
Espinoza et al. (2012)	Argentina, Mexico, Peru, Chile and USA	619 listed firms (1998-2007)	Tobit model and Generalised method of moments	Chile and the USA share determinants of capital structure, while Mexico, Argentina and Peru differ in the relevance of the determinants of capital structure.
Ramjee and Gwatidzo (2012)	South Africa	178 listed firms	Generalised method of moments	Tangibility, size, growth and risk are positively correlated with leverage, while taxes and profitability are negatively related. The study results suggest that capital structure decisions are in accordance with Pecking-order and with Trade-off theory. South African firms can adjust levels of operating leverage relatively quickly.
Oliveira et al. (2013)	Brazil	394 listed companies (2000-2009)	Ordinary least squares, Fixed effects, Quantile regression	The effects of leverage determinants vary depending on the quantile. The profitability effect is lower for less leveraged companies (lower quantile) and high for highly leveraged companies (higher quantile).
Haron et al. (2013)	Thailand	269 non-financial listed firms (2000-2009)	Partial adjustment model (PAM), Generalised method of moments	A target capital structure exists. Companies attempt to position themselves at the target, with rapid adjustment. Determinants such as size, profitability and distance from the target, influence the speed of adjustment.
Forte et al. (2013)	Brazil	19272 SMEs (1994-2006)	Ordinary least squares, Generalised method of moments	Leverage is significantly negatively related to profitability and positively related to asset growth, which is consistent with the Pecking-order theory. Other determinants such as size and age are weakly related to leverage. The coefficient of lagged leverage denotes high persistence, fitting the hypothesis that SMEs slowly adjust their debt/equity ratios towards a target value.
Gómez et al. (2014)	Peru	64 listed industrial companies (2004-208)	Random effects	Profitability and tax shield without debt are significant and negatively affect leverage. In contrast, size and collateral are significant and positively affect leverage. Therefore, the Pecking-order and Trade-off theories are evident.
Cueva et al. (2016)	Ecuador	113 non-listed manufacturing companies (2000-2012)	Ordinary least squares, Random effects	Profitability positively affects leverage, while liquidity, asset performance, and inflation have a negative effect.
Paredes Gómez et al. (2016)	Mexico, Colombia,	14 mining companies	Fixed effects, Unit roots, Cointegration	The fixed effects structure with constant slope coefficients indicates that tangibility, size and profitability are negatively and statistically significantly related to debt.

Appendix

	Chile, Brasil and Perú			
Sarmiento (2017)	Ecuador	844 manufacturing companies	Fixed effects, Random effects	Companies prefer to take on debt to take advantage of tax shields, demonstrating the influence of Trade-off theory on managers' financing decisions.
M'ng et al. (2017)	Malaysia, Singapore and Thailand	1017 listed firms (2004-2013)	Fixed effects	In all three countries, the determinants are significant and share the same sign. Profitability and depreciation are positively related to leverage, while size and tangibility are negatively related. In addition, the one-year lagged leverage has a strong positive effect.
Gutiérrez et al. (2018)	Ecuador	304 manufacturing companies (2012-2016)	Ordinary least squares, Fixed effects	The Pecking-order theory has a greater descriptive power than the Trade-off theory. There is a negative correlation among profitability, liquidity and tangibility, concerning corporate indebtedness. In contrast, size and non-debt tax shields have a significantly positive relationship with indebtedness.
Agyei et al. (2020)	Ghana	187 SMEs (2008-2013)	ordinary least squares, Fixed effects, Random effects	Profitability, liquidity, tangibility, growth, size and age significantly impact on capital structure. The effect of determinants on leverage supports the Pecking-order theory.
Spitsin et al. (2020)	Russia	1826 high-tech manufacturing and service firms (2013-2017)	Park's method and Prais–Winsten regression	The results are consistent with the static equilibrium theory since it is possible to establish an optimal capital structure. The optimal debt ratio is higher in small firms than in large ones.
Nguyen and Nguyen (2020)	Vietnam	488 non-financial listed firms (2013-2018)	Generalised least squares	The relationship between leverage and performance (return on equity, return on assets, earnings per share) is inverse and significant. However, the results behave differently for each branch of activity.
Chaklader and Padmapriya (2021)	India	171 mid-cap and 150 small-cap firms (2012-2019)	Fixed effects	Cash surpluses impact negatively on leverage, validating the Pecking-order theory. Small firms prefer to reduce long-term leverage if there are cash surpluses, while medium-sized firms reduce long-term leverage.
Utami et al. (2021)	Indonesia	154 manufacturing companies (2010-2018)	Ordinary least squares, Fixed effects, Random effects	There is a negative correlation between profitability and leverage and a positive correlation of growth and tangibility with leverage, which fits the Pecking-order theory. Dynamic, nonlinear models better explain the determinants of capital structure than static, linear ones.

Table A2. Average annual efficiency by region and non-parametric estimators.

Region	***Costa***				***Sierra***				***Amazonia***				***Galapagos***			
Year	$\hat{\phi}^{BCC}$	$\hat{\phi}^{BCC,b}$	$\hat{\rho}^{*,SBM}$	$\hat{\rho}^{*SBM,b}$	$\hat{\phi}^{BCC}$	$\hat{\phi}^{BCC,b}$	$\hat{\rho}^{*,SBM}$	$\hat{\rho}^{*SBM,b}$	$\hat{\phi}^{BCC}$	$\hat{\phi}^{BCC,b}$	$\hat{\rho}^{*,SBM}$	$\hat{\rho}^{*SBM,b}$	$\hat{\phi}^{BCC}$	$\hat{\phi}^{BCC,b}$	$\hat{\rho}^{*,SBM}$	$\hat{\rho}^{*SBM,b}$
2007	0.944	0.905	0.890	0.848	0.917	0.886	0.846	0.829	0.901	0.879	0.880	0.887	1.000	0.950	1.000	1.000
2008	0.886	0.822	0.811	0.759	0.836	0.782	0.758	0.739	0.815	0.782	0.743	0.720	1.000	0.877	1.000	0.940
2009	0.892	0.834	0.836	0.785	0.848	0.803	0.791	0.760	0.902	0.877	0.869	0.890	0.834	0.780	0.827	0.800
2010	0.853	0.796	0.788	0.729	0.855	0.801	0.799	0.771	0.897	0.855	0.865	0.884	0.804	0.738	0.718	0.600
2011	0.711	0.620	0.604	0.530	0.672	0.601	0.546	0.499	0.760	0.699	0.721	0.759	0.828	0.691	0.824	0.836
2012	0.772	0.696	0.671	0.609	0.727	0.659	0.635	0.586	0.787	0.722	0.745	0.796	0.824	0.720	0.749	0.648
2013	0.780	0.707	0.685	0.645	0.772	0.713	0.669	0.650	0.796	0.748	0.733	0.804	0.794	0.722	0.687	0.652
2014	0.717	0.641	0.611	0.562	0.679	0.610	0.583	0.525	0.784	0.725	0.616	0.597	0.870	0.713	0.856	0.767
2015	0.790	0.726	0.676	0.648	0.797	0.737	0.690	0.668	0.844	0.759	0.790	0.804	0.904	0.805	0.813	0.759
2016	0.735	0.661	0.623	0.576	0.707	0.631	0.601	0.539	0.835	0.740	0.755	0.752	0.802	0.702	0.637	0.587
2017	0.805	0.740	0.671	0.612	0.785	0.719	0.658	0.603	0.823	0.726	0.763	0.724	-	-	-	-
Average	*0.795*	*0.726*	*0.699*	*0.648*	*0.771*	*0.709*	*0.675*	*0.637*	*0.831*	*0.774*	*0.771*	*0.783*	*0.841*	*0.739*	*0.779*	*0.724*

Note: There is no data available for the Galapagos region in 2017.

Table A3. Coefficients of variation averaged by year and non-parametric estimators.

Year	DEA	Bootstrap DEA	SBM	Bootstrap SBM
2007	0.114	0.106	0.166	0.191
2008	0.160	0.141	0.239	0.253
2009	0.176	0.166	0.221	0.246
2010	0.161	0.140	0.203	0.203
2011	0.313	0.270	0.443	0.461
2012	0.238	0.195	0.329	0.316
2013	0.230	0.198	0.333	0.339
2014	0.276	0.230	0.379	0.361
2015	0.189	0.152	0.301	0.302
2016	0.282	0.245	0.394	0.365
2017	0.201	0.170	0.309	0.311
Average	*0.236*	*0.216*	*0.330*	*0.338*

Appendix

Table A4. Averaged inefficiency of inputs and outputs by region and non-parametric estimators.

Region	DEA-BCC					SBM				
	Inputs				Output	Inputs				Output
	Employees	Labor	Material	Other expenses	Revenue	Employees	Labor	Material	Other expenses	Revenue
Costa	0.090	0.040	0.020	0.011	0.006	0.385	0.356	0.252	0.212	0.001
Sierra	0.063	0.050	0.009	0.008	0.002	0.409	0.415	0.263	0.211	0.000
Amazonia	0.030	0.058	0.000	0.000	0.000	0.278	0.314	0.140	0.184	0.000
Galapagos	0.017	0.060	0.018	0.015	0.000	0.225	0.309	0.212	0.139	0.000
Average	*0.071*	*0.047*	*0.013*	*0.009*	*0.004*	*0.390*	*0.385*	*0.253*	*0.208*	*0.001*

Table A5. Inefficiency evolution over time by region and non-parametric estimators.

	DEA-BCC			SBM		
	2007	2011	2017(*)	2007	2011	2017(*)
Costa						
Employees	0.076	0.156	0.174	0.178	0.469	0.477
Labor	0.040	0.055	0.012	0.126	0.363	0.355
Materials	0.006	0.044	0.029	0.128	0.338	0.370
Other expenses	0.050	0.023	0.108	0.008	0.413	0.114
Total revenues	0.000	0.013	0.108	0.000	0.013	0.001
Sierra						
Employees	0.072	0.163	0.079	0.253	0.539	0.471
Labor	0.038	0.085	0.024	0.234	0.481	0.428
Materials	0.000	0.011	0.008	0.107	0.412	0.372
Other expenses	0.023	0.025	0.019	0.024	0.384	0.098
Total revenues	0.000	0.022	0.000	0.000	0.000	0.000
Amazonia						
Employees	0.000	0.061	0.000	0.150	0.314	0.260
Labor	0.000	0.000	0.035	0.126	0.237	0.337
Materials	0.000	0.000	0.000	0.147	0.181	0.288
Other expenses	0.000	0.000	0.000	0.059	0.386	0.064
Total revenues	0.000	0.000	0.000	0.000	0.000	0.000
Galapagos						
Employees	0.000	0.012	0.056	0.000	0.182	0.289
Labor	0.000	0.093	0.269	0.000	0.175	0.495
Materials	0.000	0.000	0.129	0.000	0.179	0.538
Other expenses	0.000	0.075	0.000	0.000	0.170	0.130
Total revenues	0.000	0.000	0.000	0.000	0.000	0.000

Notes: (*) We use 2016 inefficiencies for Galapagos since there is no 2017 data.