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"THREE ESSAYS ON APPLIED MICROECONOMETRICS"

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ÍNDICE GENERAL

CAPÍTULO 1: Resumen y conclusiones

1. Introducción y objetivo de la investigación

Esta tesis explora varias metodologías de pronóstico con múltiples tipos de datos, como series de tiempo y estadísticas transversales de fuentes confiables, datos de inteligencia de mercado, datos agregados de PoS (Post of Sales), encuestas a consumidores y cuestionarios de expertos. En resumen, la tesis tiene como objetivo mostrar cómo podemos usar estos datos para desarrollar pronósticos inteligentes y producir algunas aplicaciones detalladas. En este capítulo se discuten los esfuerzos y dificultades principales de la previsión de la demanda en la literatura y se describen los métodos de predicción más comunes que, aunque no son exhaustivos, cubren los principales enfoques en este campo. Se proporcionan algunos fundamentos de previsión de demanda, incluidos sus desarrollos y ventajas, que se usan en las aplicaciones presentadas en los capítulos 2, 3 y 4. El trabajo de investigación tiene tres contribuciones en términos de aplicaciones metodológicas específicas: utilizamos varios métodos para el ajuste de modelos con datos de panel en el capítulo 2, diversos modelos de elección discreta (DCM) en el capítulo 3 y modelos de difusión ajustados con enfoques diversos en el capítulo 4.

El capítulo 2 tiene como objetivo analizar los factores que atraen la Inversión Extranjera Directa (IED). En términos de variables independientes, utilizamos principalmente las estructuras variables adoptadas de (Nunnenkamp, 2001) investigando la importancia de los impactos de la interacción espacial, la persistencia en los niveles de IED en todas las industrias y los incentivos de política. Se consideran, asimismo, los factores convencionales como el tamaño del mercado, los costes de producción y la infraestructura como determinantes de las opciones de ubicación de la IED. El capítulo se inicia con una revisión del enfoque de pronóstico de demanda más clásico y el análisis de regresión estándar en la literatura. En primer lugar, mostramos un análisis de regresión típico y explicamos las limitaciones de utilizar mínimos cuadrados ordinarios (MCO) para estimar una regresión transversal. Demostramos que abordarlo mediante MCO no permite tener en cuenta la endogeneidad de algunos regresores, lo que resulta en estimaciones inconsistentes. También resulta que este método puede sufrir un sesgo de omisión de variables relevantes (si los efectos no observados son esenciales para explicar las variables objetivo). En consecuencia, elegimos formas alternativas de abordar este problema, utilizando datos combinados de series de tiempo y secciones cruzadas, que se configuran como un panel de datos, a los que se aplican métodos de análisis de panel como el estimador de efectos fijos (FEE) o el estimador de efectos aleatorios (REE).

El siguiente paso que se plantea en el capítulo es la aplicación de estos métodos a los Tratados de Libre Comercio (TLC) de la UE con dos países asiáticos; el TLC Corea-UE y el TLC Japón-UE. De nuevo, se aplica un análisis de regresión por MCO clásico, así como FEE. En consecuencia, realizamos un análisis de panel de las entradas de IED coreanas y japonesas en la UE. Después de aplicar los métodos de análisis de panel, analizamos los resultados de FFE y REE y discriminamos entre métodos utilizando el típico test de Hausman. Utilizando los resultados de la prueba, decidimos centrarnos más en el enfoque FEE y construir un modelo simple (que consta de impuestos corporativos y productividad laboral). Finalmente, realizamos un cuasi-experimento para examinar el contrafactual sobre el TLC UE-Japón. El modelo se estima mediante el método Diferencias en Diferencias (DID). Finalmente, extrapolamos los efectos aprovechando al máximo los datos de un TLC real UE-Corea en vigor desde 2011.

El principal objetivo del capítulo 3 es proponer una forma inteligente de analizar la demanda, las preferencias y la elasticidad de los precios de los consumidores y aplicarla en el mercado europeo de la telefonía móvil. En primer lugar, se revisamos DCM adecuados a este contexto y nos decantamos por un modelo Logit de coeficientes aleatorios (RCL, en terminología anglosajona) para la metodología de pronóstico. También exploramos plataformas para medir las preferencias de los consumidores con precisión utilizando datos a nivel agregado, que complementan los datos a nivel individual. La descripción de los modelos DCM se realiza pensando en utilizar de forma simultánea datos agregados e individuales, al tiempo que se discute la dependencia del análisis DCM de los datos a nivel microeconómico o individual. Somos conscientes que los datos públicos divulgados a nivel agregado son relativamente fáciles (y baratos) de adquirir en el mundo de Internet abierto. Sin embargo, los datos a nivel individual pueden ser costosos o, a veces, difíciles de recopilar porque los investigadores deben obtenerlos a través de datos microeconómicos como datos de puntos de venta, encuestas de preferencias y experimentos controlados. Para evitar la carga y los problemas inherentes, necesitamos una plataforma de pronóstico para medir las preferencias heterogéneas de los consumidores con datos a nivel agregado.

El siguiente paso es sugerir un enfoque para aplicarlo al caso que nos ocupa. El modelo de Berry-Levinsohn-Pakes (BLP) identifica preferencias heterogéneas de los consumidores y predice la participación de mercado con datos agregados. Dicho modelo divide la utilidad del consumidor en sus componentes homogéneo y heterogéneo. Una vez decidido el modelo, seguimos el enfoque de Nevo de aplicarlo a los datos disponibles. Medimos e incorporamos las dos preferencias diferentes con un nuevo producto en un nuevo pronóstico de mercado con múltiples datos de mercado agregados. En el análisis empírico, analizamos la preferencia de los consumidores por la industria europea de teléfonos móviles y comparamos las cuotas de mercado reales y las cuotas de mercado esperadas, así como estimamos la elasticidad precio en algunos mercados objetivo. Mostramos que el modelo BLP es una metodología adecuada, utilizando datos agregados disponibles, aunque considerando también la información sociodemográfica del consumidor. El método también es útil y ofrece una alta previsibilidad para identificar los mercados objetivo para la maximización de los beneficios. En una fase posterior, ampliamos el modelo a la segmentación del mercado desde una perspectiva empresarial. En este punto, incluimos características individuales y ambientales para tener en cuenta la heterogeneidad y utilizamos los resultados estimados para predecir cuotas de mercado correspondientes a un nuevo mercado. De acuerdo con las variables sociodemográficas, llevamos a cabo una segmentación del mercado con el fin de proporcionar evidencia de que la heterogeneidad ayuda a identificar el grupo de consumidores ideal. Luego reinterpretamos la previsión de demanda prevista y el modelo de elección para derivar los problemas de minimización de costos para los responsables de la toma de decisiones y las políticas. Tomando como base la preferencia estimada del consumidor y la información sociodemográfica, identificamos el grupo de consumidores ideal y apoyamos el establecimiento de una estrategia de marketing para maximizar los beneficios.

En el capítulo 4 se propone un enfoque metodológico basado en un algoritmo estadístico y aprendizaje automático para predecir la demanda del producto antes del lanzamiento basado en el modelo de Bass. Primero, revisamos la literatura sobre desarrollo de nuevos productos (NPD), de la que obtenemos algunas sugerencias de trabajos similares que combinan métodos de pronóstico de demanda cualitativos y cuantitativos. En el contexto de NPD, parece conveniente utilizar métodos cualitativos porque pueden ser muy flexibles y dar resultados individuales en la implementación de modelos. El éxito de la innovación está determinado principalmente por la comunicación de marketing durante el proceso de difusión. El impulso de la difusión crece lentamente hasta que alcanza el punto de inflexión, a partir del cual la velocidad de crecimiento comienza a disminuir y el mercado alcanza la saturación. En numerosos estudios, los modelos de difusión con estas curvas se han ajustado utilizando diversas bases de datos. Aunque muchos modelos de difusión son total o parcialmente exitosos al estimar estructuralmente el mercado y los parámetros subyacentes, tienden a ser muy rígidos, fundamentalmente cuando la estructura de la demanda cambia rápidamente. El modelo de Bass tiene una solución intrínseca a este problema porque podemos extraer relaciones no lineales en el conjunto de datos actualizando los datos de ventas para nuevos artículos y ajustando las previsiones minimizando el impacto de las similitudes encontradas en las estimaciones. Las especificaciones econométricas del modelo de Bass y el modelo logístico como una estructura de difusión representativos se utilizan para la aplicación empírica. Los modelos clásicos de difusión han reforzado la predicción de la difusión en términos de innovación e imitación.

Sin embargo, es fundamental tener en cuenta que los modelos clásicos están limitados en su aplicación a las innovaciones. El modelo propuesto supera esta limitación y complementa los modelos de difusión conservadores. En nuestro caso, se consideran principalmente las características del producto utilizando el modelo de difusión, y se complementa con los datos de un cuestionario a expertos, es decir, aplicando métodos Delphi. La base de datos establecida a través de este proceso es capaz de mostrar la estructura de preferencias y también proporcionar pronósticos de demanda precisos. Por lo tanto, la base de datos que seleccionamos puede predecir la situación futura del mercado cuando se lanza un producto o se introduce un servicio. Con este fin, creamos bases de datos de los atributos del producto y la difusión del producto y las utilizamos como entrada y salida. Utilizamos algoritmos de regresión estadística y aprendizaje automático, que pueden mapear con un alto nivel de confianza la relación entre los rasgos y las características de difusión de los productos existentes y, a su vez, permiten predecir la demanda de nuevos productos. Además, construimos y evaluamos varios modelos de regresión que utilizan las propiedades del producto para estimar los coeficientes de innovación e imitación del modelo de Bass, p y q. El patrón de difusión estimado proporciona una dirección adecuada para el plan de inversión desde la perspectiva de los gestores de las empresas y de los responsables de las políticas.

En la aplicación empírica, proponemos un nuevo modelo de difusión para predecir la difusión inducida, centrado en el mercado de MicroLED europeo. Desarrollamos un modelo de Bass ajustado introduciendo diferentes características del producto y aplicándolas al proceso de difusión MicroLED. También revisamos la adecuación del patrón de difusión estimado con el patrón de difusión planificado. Específicamente, elegimos 5 países europeos y la industria MicroLED como grupo de consumidores y región, con el objetivo fundamental de proporcionar una metodología eficaz de previsión de la demanda con datos de mercado a nivel agregado. Basados en modelos de difusión clásicos, creemos que el ejercicio puede apoyar la realización de la estrategia de intervención o marketing siguiendo y manteniendo el patrón de difusión.

1. fImportancia de los temas de investigación

Dos de los temas de esta tesis giran en torno a la previsión de la demanda, que tienen interés para los agentes económicos individuales, para las empresas y para los gobiernos. La previsión de la demanda siempre ha despertado un gran interés entre investigadores, analistas y tomadores de decisiones, ya que las previsiones han sido y serán fundamentales en numerosas áreas. En resumen, los agentes económicos y, los consumidores y productores, en general, están interesados en minimizar la incertidumbre o el riesgo y maximizar la utilidad, (felicidad) y el beneficio. Los desafíos aparecen con mucha frecuencia en decisiones simples o menos frecuentemente en decisiones más sofisticadas como pronosticar la difusión de COVID-19 o realizar inversiones en las que la incertidumbre sobre el retorno parece mayor puede tener efectos relevantes sobre el bienestar individual. En el mismo sentido, las empresas y los responsables de las políticas económicas invierten ingentes cantidades de dinero en capital tecnológico, infraestructuras o recursos humanos con el fin de obtener pronósticos de demanda más precisos. Tomar buenas decisiones para la demanda futura cambiará drásticamente los comportamientos institucionales, ya que las instituciones pueden influir el lado de la oferta. Por tanto, la previsión de la demanda es un proceso preliminar que resulta crucial en el proceso de decisión de planificación, I + D, logística y marketing en la oferta de nuevos productos y servicios para las empresas. Además, los responsables de las políticas económicas procuran asignar los recursos de forma eficiente, realizar estrategias de regulación adecuadas y tomar decisiones que maximicen el bienestar de los ciudadanos. En este sentido, creemos que los ejercicios empíricos seleccionados constituyen ejemplos interesantes en industrias esenciales.

El tema de la primera aplicación empírica, pronosticar el volumen de IED, es uno de los temas de la literatura más discutidos durante el TLC y la globalización. Junto con el comercio internacional, la IED ha sido considerada un motor de crecimiento económico importante en numerosos países del mundo. A nivel agregado, desde 1980 este tipo de flujos de capital privado ha crecido a un ritmo sin precedentes. Además, la IED está creciendo incluso más rápido que el comercio internacional, la economía de conexión nacional (World Investment Report). La IED es menos volátil y no muestra un comportamiento procíclico en comparación con otros flujos de capital. Por lo tanto, se ha convertido en la "entrada de capital favorita" de la mayoría de los países en desarrollo. No es sorprendente que la IED tenga una tasa de crecimiento más alta que el crecimiento anual de las exportaciones y el crecimiento anual del PIB. Por lo tanto, numerosos países pusieron en marcha políticas para promover las entradas de IED, incluida China, que anteriormente estaba cerrada a los países de inversión extranjera, y han reconocido los beneficios económicos de la inversión extranjera abriendo sus fronteras al capital extranjero. Las políticas económicas para atraer IED de las empresas multinacionales se han convertido en un estándar en la mayoría de los países. Una de las cuestiones críticas de política es: "¿qué deben hacer los responsables de la formulación de políticas para atraer IED o cuál es una regla de oro para atraer IED en general?" Es decir, ¿cuáles son las variables de política utilizadas para atraer IED? En este caso, a corto plazo, los gobiernos (los que diseñan las políticas) pueden influir directamente en las variables relevantes que tengan impacto sobre el volumen de IED. Sin embargo, a nivel de país, la pregunta más relevante a largo plazo sería: "¿Cuáles son los factores específicos del país en un período determinado que permiten atraer flujos de IED?" Sin embargo, ninguno de ellos tiende a ser consistente en varios contextos, como discutiremos más adelante. Si encontramos una variable de política relevante para la IED, debe especificarse el contexto (país socio, industria y otras variables socioeconómicas) para personalizar una política adecuada a dicho contexto.

La literatura sobre el desarrollo de modelos económicos formales de empresas multinacionales (EMN) es abundante, así como lo es la investigación empírica sobre los factores que impulsan los patrones de IED. Nuestro enfoque es llevar a cabo un análisis de regresión para datos de panel. El análisis de regresión es una de las formas más clásicas, ya que es sencilla de llevar a la práctica y permite una interpretación fácil de los coeficientes. La configuración contiene información de datos transversales e información de datos de series de tiempo, información adicional que no se puede captar solo mediante análisis de series de tiempo o análisis de secciones transversales. Por lo tanto, los datos del panel conectan las dos dimensiones. El punto esencial del análisis radica en el control de la heterogeneidad no observada de los individuos. El número de observaciones aumenta el número de grados de libertad y disminuye la colinealidad, haciendo que los estimadores sean más eficientes.

La segunda aplicación, empírica la industria de la telefonía móvil, se encuentra en el centro del mundo del Internet de las cosas (IoT) debido a la conectividad y las infraestructuras que permiten que los teléfonos inteligentes se conecten con otras máquinas o aparatos. Por tanto, la estimación de ecuaciones o sistemas de demanda del sector de la telefonía móvil es relevante ya que seguirá constituyendo un sector crítico en el futuro. Esta importancia es la razón por la que el sector de la telefonía móvil es un campo con alta innovación y rotación de clientes, donde la lucha por la cuota de mercado ha sido y está siendo feroz. Si bien diversos tipos de investigación académica se ocupan de la industria móvil y la estrategia de marketing de los operadores y fabricantes desde la perspectiva empresarial, numerosos estudios todavía se centran en los operadores de red debido a su fuerte influencia en la cadena de valor. (Dedrick, et al., 2011) muestran que Apple ofrece buenos ejemplos de ganancias y reinversión en estos sectores, capturando una gran parte del valor de la marca. Además, la llegada de los teléfonos inteligentes Apple y Android hizo que el papel de los fabricantes se volviese crucial en términos de competencia. Desde la primera década del siglo, el mercado de la telefonía móvil está creciendo rápidamente y las ventas alcanzaron casi los 2.000 millones de euros anuales, solo en la Unión Europea (UE). En consecuencia, a pesar de las altas barreras de entrada debido a la tecnología y los requisitos de capital intensivo, cada vez más fabricantes se unen al mercado con el fin de ganar cuota de mercado. Hubo ganadores y perdedores en esta industria desde el comienzo del nuevo milenio. Sin embargo, después de 2010, la competencia se ha tornado todavía más fuerte. Una de las razones importantes es que los fabricantes chinos están bien equipados con alta tecnología y experiencias de su gran mercado interno, apuntando al mundo entero. Incluso si el crecimiento parece que se estabilizó y estaba maduro para 2015, la demanda esperada de las economías emergentes y los efectos indirectos (que harán que los teléfonos inteligentes faciliten dispositivos relacionados en el futuro) hacen que esta industria siga siendo atractiva.

Para muchos fabricantes, el mercado de la telefonía móvil ya no es una fuente de ingresos ni de ganancias debido a esta competencia desatada. Si bien estos productos, incluidos los producidos en China u otros países en desarrollo, los principales beneficios se reinvierten en su diseño de productos, desarrollo de software, gestión de productos y marketing. Sin embargo, el principal requisito previo de la inversión tanto en I + D como en marketing es el beneficio; por lo tanto, muchos fabricantes se esfuerzan por encontrar espacio para más ganancias reduciendo los costes y aumentando los precios de venta. Por lo tanto, la reducción de costes a través de la optimización de la producción, la agilización de procesos y la logística es un tema preferente en numerosas empresas electrónicas. Sin embargo, es difícil abandonar el mercado móvil debido a 1) su gran tamaño, 2) los altos costes irrecuperables de inversión y 3) el efecto desbordamiento a otras áreas futuras relacionadas con la electrónica en el mundo del IoT. En un mercado perfectamente competitivo como el de los productos básicos, la teoría microeconómica sugiere que los fabricantes no encuentren espacio para obtener beneficios. Por tanto, los fabricantes tienen una gran motivación para optimizar sus estrategias de precios, lo que les permitirá reinvertir y sobrevivir en la industria. La estrategia de supervivencia a largo plazo de un fabricante de teléfonos móviles debería ser la diferenciación. 1) invertir en I + D para hacer que su producto sea único y 2) invertir en marketing para mejorar el valor percibido de sus productos y construir una imagen de marca diferenciadora para que los consumidores eviten la competencia, es decir, aumentar el conocimiento de la marca, la exposición del producto (PR).

El enfoque directo que seguimos en esta aplicación empírica es combinar la literatura del marketing y la economía industrial sobre la industria móvil para construir los conceptos básicos y poder estimar modelos de demanda heterogéneos. Presentamos brevemente las estadísticas generales para comprender mejor el mercado y proponemos modelos logit y logit de coeficientes aleatorios (RCL) para estimar las ecuaciones de demanda, ya que consideramos que el RCL es un enfoque atractivo para ello en el caso de compras discretas a partir de datos agregados. Para ellos seguimos la metodología de BLP (Berry, et al., 1995) y (Nevo, 2000), basada en la observación del mercado y el formato agregado de los datos de inteligencia de mercado. Utilizando supuestos y metodologías de la estructura BLP, proporcionamos un método práctico para estimar las elasticidades-precio para sistemas de demanda que involucran muchos conjuntos de datos similares utilizando datos de inteligencia de mercado. El modelo BLP también permite que las aplicaciones a otros productos electrónicos relacionados sean relativamente simples, considerando las similitudes en las características, la naturaleza perecedera de los precios de venta, la demanda heterogénea y las diferencias demográficas en los gustos. Además, para hacer frente a la debilidad de dicho modelo, la alta dimensionalidad, ejecutamos la mayoría de los procesos de cálculo en Amazon Web Service, las plataformas de computación en la nube bajo demanda de última generación y las API.

La tercera aplicación en el capítulo 4 gira en torno a la predicción de los ciclos de vida de los nuevos productos de la Electrónica del Consumo (CE) y MicroLED. Para la estimación de la demanda de esos productos innovadores la literatura sugiere análisis de regresión, modelos logit, suavizado de tendencias históricas y modelos estocásticos de series de tiempo. El proceso de innovación es ahora crucial para innovaciones radicales, incrementales, realmente nuevas, discontinuas e imitativas y diseños arquitectónicos, modulares, de mejora y evolutivos. Este hecho es especialmente relevante para la CE, donde es fundamental que las empresas lo utilicen para planificar futuras inversiones, mantenimiento y disposición de recursos. Debido al rápido envejecimiento u obsolescencia, muchos bienes de consumo tienen una vida corta. La ley de Moore todavía se mantiene en el siglo XXI, y la potencia informática crece simultáneamente. Por supuesto, esto brinda a las empresas tecnológicas más oportunidades para desarrollar ideas que aprovechen al máximo estos avances para atraer a más consumidores. Como consecuencia de ello, el mercado de la CE parece estar explotando. Los expertos esperan que las ventas anuales de CE a nivel mundial alcancen los 2,9 billones de dólares en 2020. Nuevos productos, como teléfonos inteligentes, televisores OLED u ordenadores en la nube, han evolucionado y crecerán a gran velocidad. Para atraer las preferencias de los consumidores, las empresas de CE están buscando nuevos tipos de productos. Muchos productos que supuestamente son "completamente nuevos" son, de alguna forma, variaciones de productos existentes; muchos conglomerados de electrónica ya cuentan con la tecnología para fabricar cualquier producto que se adapte mejor a las necesidades de los clientes. En consecuencia, productos de consumo, como los electrónicos y tecnológicos, tienen ciclos de vida cortos, se vuelven obsoletos rápidamente, se han de actualizar con frecuencia y ofrecen numerosas alternativas competitivas. El punto crucial en la previsión de nuevos productos de CE exige comprender la relación entre las decisiones de producción de los fabricantes y el comportamiento dinámico del consumidor.

MicroLED es una nueva tecnología de pantalla emergente. La pantalla consta de filas de LED microscópicas que forman los elementos de píxeles individuales. En comparación con la tecnología LCD ampliamente utilizada, microLED ofrece un mejor contraste, tiempos de respuesta más rápidos y una mayor eficiencia energética. Durante el Consumer Electronics Show (CES) de EE. UU. de 2018 – 2020, varios fabricantes exhibieron televisores MircoLED . Además, es un hecho conocido que incluso otros fabricantes sin producción de televisores como Apple y Oculus adquirieron empresas MicroLED debido a su importancia. MicroLED es una nueva tecnología similar a OLED ya que cuenta con pantalla autoemisora, que permite producir pantallas aún más brillantes y eficientes. Actualmente no hay pantallas MicroLED en producción en masa, pero muchos fabricantes ya prueban y cuentan con esta tecnología. Los expertos creen que MicroLED tiene el potencial de desafiar a OLED en el futuro. La razón no se debe solo a las ventajas mencionadas anteriormente, sino que no tiene efectos de quemado de OLED ya que no usa material orgánico en el píxel sino un material inorgánico como nitruro de galio (GaN). Los MicroLED son extremadamente pequeños, típicamente 1/10 del ancho de un cabello humano, lo que permite que se depositen como una matriz de píxeles sobre un sustrato para hacer una pantalla. Será extremadamente competitivo en el futuro, ya que muchos fabricantes (como Sony, Samsung, LG, Apple) están interesados en MicroLED. Mientras que los fabricantes coreanos como LG y Samsung ya se están preparando para la producción en masa y aumentando las inversiones, Epistar y Leyard Opto-Electronics tienen la intención de construir un Micro-LED de 142 millones de dólares, y Konka anuncia un centro de I + D de micro-LED de 365 millones de dólares. MicroLED podría finalmente reemplazar el mercado actual de LCD y OLED en el futuro. Por lo tanto, predecir el ciclo de vida y la demanda de MicroLED puede proporcionar información valiosa para desarrollar tecnologías relacionadas, establecer planes de producción y desarrollar estrategias de marketing. MicroLED es extremadamente difícil de fabricar a gran escala y requiere mucha inversión, lo que implica que existe la posibilidad de pronosticar la distribución de la demanda de MicroLED con anticipación. Con patrones de sustitución drásticos y crecientes incertidumbres del mercado, y la ingente cantidad de inversión necesaria, la capacidad de predecir la distribución de la demanda MicroLED y CE por adelantado proporciona valiosos apoyos para la toma de decisiones. Las previsiones son, por tanto, importantes para planificar la entrega de nuevos productos, la logística y las inversiones. Las predicciones precisas respaldan la puesta en práctica de estrategias y pautas de marketing, mientras que las predicciones incorrectas conducen a la pérdida de recursos.

El enfoque que seguimos para abordar esta aplicación es combinar la literatura del marketing y la economía industrial sobre CE y MicroLED. Para predecir las ventas de nuevos productos, analizamos el desempeño de las ventas de los grupos anteriores y realizamos estudios de similitud en los artículos de estas colecciones, lo que brinda una poderosa herramienta de aplicación. Es crucial, por tanto, determinar los componentes y medir la similitud. Podemos definir y encontrar similitudes de diversas formas. Una de más efectivas es vincular los pronósticos de nuevos productos con los datos históricos de los productos con atributos estrechamente relacionados. En este caso, es posible que encontrar similitudes en las muchas industrias aparentemente relacionadas y no relacionadas sin considerar que estas características no captan suficientemente toda la complejidad del procedimiento de pronóstico. Por lo tanto, ha habido enfoques para medir esas similitudes cuantitativa y estructuralmente. (Lee, et al. 2014) y (Ganjeizadeh, et al. 2017), por ejemplo, proporcionan el concepto de características y atributos de producto donde nuevos productos pueden heredar el comportamiento en ventas de características de producto similares. Una vez definidas las similitudes, se pueden utilizar métodos cualitativos para capturar la tendencia de la demanda basándose en un análisis estadístico de datos de mercado en el pasado. Después de esta fase, las técnicas cuantitativas podrían proporcionar resultados satisfactorios utilizando datos masivos para las predicciones. En este contexto, seguimos el marco propuesto por (Lee, et al. 2014). Primero, creamos la base de datos de productos definiendo los atributos críticos de los productos para medir las similitudes de los productos en la base de datos de demanda y la construimos a partir de datos de inteligencia de mercado, PoS, metaanálisis o encuestas a expertos, centrándonos principalmente en la industria CE. Luego, realizamos un pronóstico de demanda previo al lanzamiento para MicroLED basado en el modelo Bass, combinado con métodos de aprendizaje automático (ML). Identificamos varios atributos como variables independientes y estimamos los coeficientes de innovación, p, y difusión, q, como variables dependientes utilizando la base de datos de demanda de productos.

El aspecto que implica el mayor desafío de esta investigación es la adaptación del modelo Bass para nuevos productos para estimar los parámetros correctos de un nuevo producto con escasa (o nula) información histórica de ventas disponible. El enfoque convencional para el pronóstico previo al lanzamiento es el uso de análisis análogos o similares. Tratamos de encontrar estadísticas de participación de mercado con productos relacionados y sus datos históricos. También utilizamos los resultados de los cuestionarios para obtener los atributos relevantes para todos los productos disponibles, así como para Micro-LED frente a otros productos para la aplicación empírica. Llevamos a cabo la estimación de parámetros utilizando el aprendizaje automático. Nos centramos en 11 métodos diferentes y analizamos sus ajustes y los comparamos. En un proceso posterior, utilizamos la base de datos construida y los métodos para estimar la demanda de Micro-LED. También aplicamos otros métodos de aprendizaje automático de última generación para determinar coeficientes con el fin de aprovecharlos al máximo, incluyendo la efectividad del algoritmo de ML en el área de pronóstico y el aumento actual de los poderes de computación en la nube a través de GPU. También mostramos un análisis de apariencia convencional para el pronóstico de demanda de MicroLED que mezcla datos de otros productos de la misma categoría. Finalmente, discutimos cómo el marco metodológico propuesto en este trabajo supera las limitaciones de los modelos anteriores, en particular su incapacidad para adaptarse a la heterogeneidad del consumidor y para predecir la demanda de nuevos productos que reflejen la complejidad del mercado. Los resultados podrían permitir a los fabricantes tomar decisiones estratégicas para desarrollar el marketing de productos que posibilite a los responsables simular la evolución del mercado de la televisión, preparándolos así para el lanzamiento de estos productos al mercado.

2. Fundamentos teóricos y metodología

3.1. <u>Marco teórico</u>

Existen en la literatura numerosos modelos y métodos en los que encajar la investigación que se presenta en esta tesis doctoral. El primer modelo que podemos relatar para ello está basado en la aplicación de técnicas cualitativas (métodos de juicio, subjetivos o, a veces, discretos), que utilizan datos cualitativos (es decir, opinión de expertos y cuestionarios, teoría de juegos, experimentos de mercado, técnica Delphi, análisis morfológico, encuestas a consumidores) e información sobre los eventos especiales del tipo ya mencionados y que pueden o no considerar el pasado. Tendemos a predecir la demanda mediante la recopilación de datos sobre el comportamiento de compra de los consumidores, de expertos o realizando encuestas, pequeños experimentos con objetivos o actividades similares. Este método abarca los planes de compra futuros y las intenciones de los consumidores a través de encuestas a los consumidores para determinar la demanda de sus productos y servicios existentes y, en consecuencia, anticipar el futuro. Entre estos métodos cabe citar, sin pretensión de exhaustitivad el método de opinión de expertos, también conocido como "método de consenso de expertos", que utiliza los resultados de la investigación de mercado. En el último capítulo de la tesis mostramos que las estimaciones algebraicas basadas en métodos de opinión de expertos muestran una conversión razonable y eficiente del conocimiento y la experiencia en parámetros del modelo. Además, bien diseñado y resumido, podemos convertir rondas de encuestas de forma rápida y precisa para estimar los parámetros del modelo de Bass. La comprensión de los modelos matemáticos por parte de los expertos parece diferir debido a la diversidad de sus antecedentes y experiencia profesional.

Por otro lado, el método Delphi intenta llegar a un consenso sobre el pronóstico a través de discusiones repetidas mediante preguntas individuales a los expertos para determinar su opinión sobre la demanda futura de productos, que terminan en un consenso, ya que se proporciona a cada experto información sobre las estimaciones de otros expertos para revisar sus estimaciones en función de dichas estimaciones alternativas. La principal ventaja de este método es que es rápido y económico, ya que los investigadores pueden contactar con múltiples expertos en poco tiempo sin utilizar otros recursos, pero cuenta con la desventaja de poder conducir a decisiones subjetivas.

Los experimentos de mercado son ampliamente utilizados y son prácticos para la predicción de los efectos de los cursos de acción alternativos, ya que recogen la información necesaria acerca de la demanda actual y futura de un producto. Cuando la recopilación de datos no es posible, el *bootstrapping* de juicio(*judgment bootstrap*) también utiliza la opinión de expertos valorando, asimismo un modelo de pronóstico mediante preguntas que faciliten la información que dichos expertos utilizan para hacer predicciones en situaciones de este tipo. En una segunda etapa, se les piden que hagan predicciones para una variedad de casos reales e hipotéticos, lo que posibilita la estimación del impacto de cambiar variables clave cuando los datos históricos son insuficientes para permitir dichas estimaciones. Los modelos de bootstrapping de juicio aplican consistentemente las reglas de un experto, y existen estudios numerosos que han demostrado que las decisiones y predicciones de los modelos de bootstrapping son similares a las de los expertos.

Finalmente, existen métodos cualitativos experimentales basados en la teoría de juegos (Armstrong, et al., 2015), métodos de análisis conjunto, también descrito como análisis de preferencias (Green, et al., 2001), métodos de análisis de índices, que se centra en una limitado número de alternativas para predecir la selección cuando se requieren respuestas rápidas a la evolución futura de la demanda de un producto.

Todos los enfoques cualitativos son evaluaciones subjetivas de evaluadores y expertos. Este proceso puede llevar a una sobreestimación o subestimación y tiene muchas limitaciones ya que se utilizan las opiniones personales para extraer conclusiones, cuando los datos y la aplicación de métodos cuantitativos pueden obviar dichas opiniones, algo que resulta muy relevante si se han de realizar previsiones a largo plazo. El análisis cuantitativo predice la demanda mediante técnicas estadísticas utilizando datos previos que, usualmente, requieren un largo historial. El análisis cuantitativo supera esta limitación del análisis cualitativo utilizando datos y modelos. Un sistema avanzado para superar los límites del análisis cuantitativo es combinarlo con otro método matemático con antecedentes teóricos (Clemen, 1989). Por lo tanto, el análisis cualitativo y cuantitativo se puede utilizar de manera complementaria para una mejor predicción.

Las técnicas cuantitativas pueden ser clasificadas de muy diversas formas, pero a los efectos de esta tesis lo haremos en modelos de series de tiempo y modelos causales. La principal diferencia es que los métodos de series temporales extraen toda la información de los datos históricos, mientras que los modelos causales aprovechan al máximo los conocimientos y la teoría previos. La clave es identificar las variables críticas, la dirección de sus efectos y cualquier limitación. Los modelos causales son más útiles cuando esperamos fuertes relaciones causales entre variables dependientes e independientes, y las relaciones causales son conocidas o pueden estimarse. Uno de los enfoques integrados más conocidos es el DCM. En este contexto de elección se asume que los consumidores deciden maximizar su utilidad (por ello también se denominan modelos aleatorios de utilidad). El DCM se utiliza para establecer una nueva metodología para pronosticar la demanda con consumidores que tienen preferencias heterogéneas. Según (Luce, 1959) el modelo de selección discreta con maximización de la utilidad concuerda con la fórmula logit y (McFadden, 1974) facilita la teoría econométrica y su aplicación empírica de DCM. En la literatura, encontramos DCM ampliamente para pronosticar la demanda en función del comportamiento y las preferencias del consumidor. El DCM puede calcular la cuota de mercado basándose en la simulación del modelo de selección, como mostramos en el capítulo 3. Sin embargo, el modelo de selección solo puede proporcionar información sobre la probabilidad de selección a través de las preferencias del consumidor. Los investigadores necesitan una estimación del potencial real del mercado para obtener un pronóstico de demanda completo. Un problema común con el análisis DCE es que la estimación requiere de grandes conjuntos de observaciones de la máxima frecuencia temporal (a poder ser diarias) para determinar las preferencias del consumidor.

Para poder aplicar DCM, se necesita realizar encuestas y sabemos que las encuestas pueden causar un problema de sesgo hipotético si los encuestados están informados sobre un producto, siempre indicarán una mayor disposición a pagar en una situación virtual que en una situación de mercado real (problema de *stated preferences* frente a *revealed preferences*). Además, no podemos ignorar que las encuestas pueden ser muy costosas y requerir demasiado tiempo, lo que convierte las predicciones en poco útiles. El modelo BLP de (Berry, et al., 1995) utiliza principalmente datos a nivel agregado, introduciendo perturbaciones a nivel individual para incrementar su flexibilidad y superar sus limitaciones implícitas. (Nevo, 2000) desarrolla aún más el modelo RCL. Por otro lado, podemos usar los modelos de difusión para predecir las demandas de un nuevo producto o servicio con solo unas pocas observaciones. Este es el tipo de metodología que se utiliza en los capítulos 3 y 4, combinada con procedimientos y algoritmos que optimizan la utilización de datos masivos y modelos de difusión (Bass, 1969).

(Varian, 2014) dividió el análisis de datos en estadística y econometría y fortaleció el poder del ML principalmente para la predicción. ML utiliza diversos tipos de herramientas para sintetizar significativamente diferentes tipos de relaciones no lineales en los datos. ML tiene un buen número de beneficios para pronosticar las demandas cambiantes (Croker, 2009). La mayor fortaleza de ML es proporcionar sistemas informáticos de alto rendimiento, que pueden ofrecer predicciones útiles en condiciones informáticas severas. A medida que ML y el hardware / software de los ordenadores han logrado un progreso significativo en los últimos años, las aplicaciones en la demanda de modelos de productos de consumo están aumentando de forma exponencial. Los métodos ML son también muy flexibles ya que permiten trabajar con datos estructurados y no estructurados, en estudios de marketing, con cifras macroeconómicas y con datos de noticias de redes sociales y medios de comunicación. En una de las aplicaciones seguimos el espíritu de (Lee, et al., 2014) para construir una base de datos de demanda de productos que incluye sus características que representen el ciclo de vida basado en productos existentes, para aplicar métodos de estimación de ML. Finalmente, un método Deep Learning (DL o las redes naturales de aprendizaje profundo) usa métodos informáticos que utilizan procesos de toma de decisiones análogos a los que se utilizan en el cerebro humano. El DL se constituye en un tipo de redes neuronales artificiales (ANN) que imitan la lógica del cerebro humano (Haykin, et al., 2009).

3.2. Métodos

En el Capítulo 2, seguimos el modelo de (Driffield, 2002), donde los beneficios futuros esperados para estimar modelos econométricos con datos de panel para ajustar flujos de inversión extranjera (Π^c) impulsan fundamentalmente la probabilidad de que una empresa entre o se expanda en un país de la UE . Dada una vida útil de la inversión de períodos T y la tasa de descuento, r, podemos escribir ϕ_2, siguiendo a (Driffield, 2002), en función de las características del país: $\sum_{p=0}^{T}\left(\frac{r}{\mathrm{r+1}}\right)^{p}\Pi_{t+p}^{c} \quad = \phi_2(X_{1i}, X_{2i})$. X_{1i} son variables que se cree que están relacionadas positivamente con las utilidades (rentabilidades), y X_{2i} variables postuladas para reducir la rentabilidad esperada. De la ecuación previa podemos derivar un modelo lineal para los determinantes de la IED en la UE, que podemos escribir como: $y_{it} = \alpha_i + x_{it}\beta + \epsilon_{\mathrm{it}}$ donde y_{it} = entrada de IED / PIB para el país i en el período t.

En el Capítulo 3, dado que nuestro principal objetivo es estimar un modelo de demanda completo, partimos del conocido modelo logit agregado clásico; luego, pasamos al modelo agregado de RCL. Suponemos un conjunto de mercados, m = 1,…, M, donde el mismo conjunto de productos, j = 1,…, J, está disponible en cada mercado (y / o tiempo). Denotamos no comprar por j = 0 y los individuos por i = 1,…, N (N es grande).

En el capítulo 4, comenzamos con el modelo de Bass (Bass, 1969) para predecir la demanda correcta de nuevos conceptos y otros atributos (relacionados con la tecnología o los productos) antes de que su lanzamiento brinde ventajas a consumidores, decisores y empresas. El modelo de difusión más representativo descrito anteriormente, el modelo de Bass, que utilizamos para realizar análisis de difusión específicos del producto. Hay muchas formas de formular el modelo. En resumen, el modelo consta de dos parámetros básicos. Por un lado, el coeficiente de innovación (p), que captura la importancia relativa de los clientes innovadores para generar ingresos por la venta del nuevo producto. Por otra parte, el coeficiente de imitación (q), que captura la esencia cercana de los clientes en la imitación que ayudan a las empresas a realizar ventas del nuevo producto. El modelo funciona de tal manera que, independientemente de los valores de p y q, a medida que más y más clientes aceptan o compran el nuevo producto, el impacto relativo de imitar las compras de los clientes juega un papel más crítico en la determinación de la curva de ventas.

3. Conclusiones y extensiones

En esta tesis se han explorado algunos métodos microeconométricos de previsión con diversos tipos de datos, de encuesta, meta-análisis, de series temporales, de sección cruzada etc., para tratar de mostrar su utilización para realizar predicciones adecuadas y se han realizado tres ejercicios empíricos.

El capítulo 2 analiza el TLC UE con Corea y Japón, y se aplican formas de modelización utilizando la configuración de análisis de datos de panel. Estimamos varias especificaciones de modelos con el fin de ajustar los determinantes de los flujos de inversión extranjera directa. Se emplea un conjunto de datos sobre IED descargado de Eurostat y se considera la IED como variable dependiente. Asimismo, se utiliza un conjunto completo de variables explicativas de diversas fuentes como UNstat y Banco Mundial. Los métodos OLS, el modelo de efectos aleatorios y los estimadores de efectos fijos ajustan los determinantes de la IED coreana y japonesa a Europa. Las especificaciones finales consideran modelos de efectos aleatorios para Corea y Japón. Se prueba con veintiséis países europeos y las especificaciones contienen un buen número de factores como variables explicativas potenciales, muchos de los cuales resultan significativos. A diferencia de otro tipo de literatura, muchas variables independientes (como el PNB per cápita, el tamaño de las zonas francas, el apoyo a las políticas, la tasa salarial, la tasa de inflación, el costo de transporte / infraestructura) que resultaban significativas con datos de EE. UU., países de África y Europa han sido no relevantes en la explicación de la IED, fruto de la consideración de los efectos de país. Dicho de otra forma, los efectos de país pueden enmascarar efectos de otras variables y, en consecuencia, su control es muy relevante para obtener estimadores consistentes de los efectos de las variables relevantes.

En primer lugar, realizamos un análisis de panel de la entrada de IED coreana. Después de las pruebas de Hausman, el método elegido es el que asume que los efectos de país son aleatorios. Numerosas variables tienen significación estadística, como el tiempo de trámite (-193%), el impuesto de sociedades (-120%), la desigualdad de ingresos (-121%) y el coste laboral (-334%), que presentan coeficientes negativos de gran magnitud y con significación estadística. A diferencia del escenario UE-Corea , la introducción del euro tuvo un impacto muy positivo (1,101%) en la entrada de IED. En la regresión con indicadores de país, solo la apertura tuvo un coeficiente positivo (31%). En la regresión con los indicadores de la institución, mientras que tiempo dedicado a burocracia (-124%), el Impuesto sobre Sociedades (-60%) y el IVA (-21%) tienen un fuerte impacto negativo, la productividad (193%), la educación (8%) y la facilidad para hacer negocio (4%) tienen impactos positivos. En la regresión con indicadores económicos, mientras el coste laboral (-600%) tiene un fuerte impacto negativo, la Balanza de Pagos (73%) tiene impacto positivo. Este resultado significa que los inversores surcoreanos estarían muy interesados en ser capaces de incidir sobre estos indicadores. En segundo lugar, realizamos un análisis de panel de la entrada de IED japonesa. Tras el contraste de Hausman, se concluye que el estimador de efectos aleatorios proporciona mejores resultados económicos y estadísticos. El tiempo dedicado a burocracia (-42%), el Impuesto sobre Sociedades (-24%), la Balanza de pagos (-18%) muestran coeficientes negativos relevantes en magnitud y significatividad. El euro tuvo un impacto muy positivo (296%) en la entrada de IED. En la regresión con indicadores de país, solo la apertura tuvo un coeficiente positivo (33%). En la regresión con indicadores de instituciones, mientras que el tiempo de trámites burocráticos (-41%), el Impuesto de Sociedades (-34%) y el IVA (-485%) tienen un fuerte impacto negativo. En la regresión con indicadores económicos, tanto el coste laboral (-3,672%) como la Balanza de Pagos (-690%) tienen fuertes impactos negativos, en este último caso, un resultado contrario a la intuición económica.

Finalmente, realizamos el cuasi-experimento para analizar el impacto contrafactual de la IED japonesa con la UE. Sobre muchas combinaciones de determinantes, el impuesto de sociedades y la productividad laboral mostraron buena capacidad explicativa; con este modelo simple, realizamos un análisis DID para mostrar el impacto del TLC entre Corea y la UE en la IED coreana. Después del análisis DID, se mide el 317% (regresión de panel con variables ficticias) el impacto puro del impacto del TLC en la IED. Desde el TLC Japón-UE, la UE podría recibir un 732% adicional de IED de Japón. También extrapolamos similitudes y diferencias entre la afluencia coreana y japonesa. Con el fin de incentivar la IED los decisores pueden centrarse en la productividad del trabajo y en el la reducción de los impuestos, el de sociedades y el IVA. El TLC promueve el comercio y el intercambio de conocimientos entre bloques económicos; también promueve la entrada de IED y el impacto de inversión para la UE fue beneficioso, de más del 300%, después de firmar el TLC con Corea. Mediante la firma de TLC con Japón, la EU podría recibir más de un 700% adicional de entrada de IED japonesa a la UE.

En términos de implicaciones de política económica que se pueden extraer de los resultados obtenidos en el ejercicio, nuestras propuestas para fortalecer la evolución futura de la IED en la UE son: a) la continuidad y la profundización de las relaciones UE-Corea y Japón con el fin de fortalecer la IED, dados los resultados del análisis DID, aunque somos conscientes que la utilización de datos de empresas podría contribuir a dar robustez a los resultados de impacto obtenidos. b) Avanzar en la cooperación con otros países, es decir, utilizar la misma configuración en otros casos de IED (de país a país), especialmente en los casos de Brasil, India, China y Rusia (los denominados) BRIC a la UE.

El capítulo 3 presenta un ejercicio sobre la demanda en la industria móvil de varios países de la UE. Primero mostramos por qué los métodos y resultados del trabajo serían útiles para individuos relacionados con la industria móvil o con el ajuste de la demanda en dicha industria, como, por ejemplo los responsables políticos nacionales o europeos. La especificación se realiza utilizando observaciones de mercado, datos demográficos microeconómicos, y datos de inteligencia de mercado agregados. La metodología ofrece, desde el punto de vista computacionalmente, un importante desafío. Se estiman modelos logit y RCL siguiendo la metodología de BLP / Nevo de compras discretas a partir de datos agregados. Aprovechamos al máximo estos datos de diversas fuentes para tratar de comprender los modelos estáticos de demanda en la industria de la telefonía móvil. Mediante el uso de datos macroeconómicos que coinciden con el supuesto de distribución para ajustar la demografía en cada país, enriquecemos dichas especificaciones. Tras el análisis cuidadoso de los datos brutos, se seleccionaron datos de 98 productos en 12 países europeos para un período de 36 meses consecutivos. Además, se realizaron diversos supuestos y tests para construir instrumentos adecuados tomando información desde el lado de la oferta.

El modelo RCL revela resultados muy significativos. Las estimaciones sin datos demográficos muestran que, con carácter general, los teléfonos móviles en los países europeos se venden bien si sus precios son bajos. Los resultados, incluida la demografía, muestran varias conclusiones heterogéneas por país, de lo que se deduce una implicación muy relevante de que los resultados muestran que la heterogeneidad en las preferencias es importante para el comportamiento del consumidor en la industria de la telefonía móvil en un país específico. Además, se observa nítidamente que los consumidores son sensibles a precios y renta. Por otra parte, los resultados sugieren que la edad (en número y el umbral de 18 años) es un determinante crucial del comportamiento individual en demanda de teléfonos móviles. Presentamos algunos resultados del modelo de demanda de RCL a nivel agregado y de mercado. En el marco de (Nevo, 2000), estimamos las elasticidades precio como un subproducto de la estimación de los parámetros de la demanda. Con ello se muestra que el enfoque utilizado y el análisis pueden resultar interesantes para los gerentes de producto quienes deben establecer precios y carteras de los productos y para los responsables de las políticas, quienes deben evaluar objetivamente la regulación del mercado.

Una contribución significativa del enfoque utilizado consiste en proporcionar un método práctico para estimar las elasticidades de los precios para los sistemas de demanda que involucran muchos conjuntos de datos similares utilizando datos de inteligencia de mercado. Las aplicaciones a otra industria electrónica relacionada serían relativamente simples como muestran, por ejemplo, (Aguirregabiria & Ho, 2012), considerando las similitudes en las características, la naturaleza perecedera de los precios de venta, la demanda heterogénea y las diferencias demográficas en los gustos. La literatura muestra que los investigadores y las empresas han utilizado técnicas estadísticas y modelos RCL para la estimación de sistemas de de demanda, utilizando series históricas de ventas como principal fuente de datos. Nuestro trabajo presenta un ejemplo de aplicación del modelo BLP clásico con un uso inteligente de la estimación y restricciones de variables instrumentales mientras se avanza hacia tecnologías novedosas, como la nube de Amazon Web Service y el paquete BLPestimatoR de última generación.

El capítulo finaliza sugiriendo algunos posibles desarrollos futuros: Estimaciones y pronósticos utilizando algunos algoritmos ML en la configuración BLP / Nevo. Ya encontramos algunos enfoques para aprovechar al máximo las tecnologías más nuevas en la literatura utilizando ML. Los pronósticos de demanda de ML a veces pueden mostrar resultados de mejor calidad que las técnicas tradicionales como sugieren (Xu, et al., 2018). Por tanto, los modelos de ML pueden ir acompañados de BLP porque BLP muestra actuaciones más potentes en muchos contextos (Badruddoza & Amin, 2019). Además, la interpretabilidad es una de las ventajas esenciales de los modelos RCL utilizados y de modelos estructurales, en general, en comparación con el aprendizaje automático. Por lo tanto, creemos que la utilización de ML dentro de la configuración de BLP / Nevo o en general de RCL puede extraer información útil de datos agregados como coeficientes, la relación entre variables y elasticidades de precio propias / cruzadas de productos mejorando el desempeño de la metodología de estimación.

El capítulo 4 se centra en el análisis de la previsión de la demanda de MicroLed utilizando el modelo de Bass. Los modelos de difusión son los modelos más populares en la literatura para pronosticar la aceptación por parte del mercado de un nuevo producto / servicio. Además, el modelo Bass es flexible (únicamente contiene tres parámetros) y es adecuado para predecir la introducción de nuevos productos en analogía con los existentes. Sin embargo, la estimación de parámetros ha sido un punto de fricción en este contexto porque hay datos limitados (o incluso a veces no existen) de series de tiempo disponibles para nuevos productos. Sin embargo, una base de datos con las características del producto y los nuevos valores parametrizados del modelo Bass constituye una solución. Proponemos un enfoque basado en un algoritmo estadístico y ML para predecir la demanda del producto antes de su lanzamiento basado en el modelo de Bass. El marco principal comienza con un enfoque similar a la propuesta de (Lee, et al., 2014), que construyen una base de datos con los datos de demanda disponibles. Con muchos datos de transacciones e inteligencia de mercado, podemos aprovechar al máximo estos modelos, obteniendo datos de demanda de productos adicionales y bases de datos de atributos, que permitan realizar predicciones ajustadas de demanda de nuevos productos.

Además, utilizamos métodos Delphi con varias rondas de cuestionarios (Kim, et al., 2013) y un metaanálisis (Sultan, et al., 1996) para complementar la base de datos de productos. Como resultado de la aplicación de estos métodos, optimizamos la base de datos de las características de productos (Kim, et al., 2013) y (Lee, et al. 2014). En una siguiente etapa, se importan módulos de ‘sklearn’ para utilizar Python scikit-learn enteramente junto con otros módulos Python y TensorFlow 2,0 para las estimaciones de los parámetros. El modelo de conjunto mejora aún más la precisión de las predicciones. Se desarrolla un modelo de predicción utilizando seis algoritmos de ML. Posteriormente, se utilizan modelos de conjuntos basados en 11 modelos de predicción general para mejorar la capacidad predictiva. Con este espíritu, hemos construido y evaluado 11 modelos de regresión que utilizan las propiedades del producto para predecir los parámetros p y q del modelo de Bass. Son algoritmos de regresión representativos ampliamente utilizados en economía, estadística y aprendizaje automático: Regresión Lineal Múltiple (MLR), Regresión Ridge, Regresión de Lasso, Árboles de Clasificación y Regresión (CART), Bosques Aleatorios (Ramdom Forest), AdaBoost, Regresión Impulsada por Gradiente (GBR), Regresión Impulsada por Gradiente Generalizada (XGBR) y Aprendizaje Profundo mediante TensorFlow y Keras . Como resultado de evaluar el rendimiento predictivo de un solo modelo de regresión, el bosque aleatorio y la regresión de aprendizaje profundo muestran el mejor rendimiento predictivo en términos de tres indicadores de NMSE. Después de numerosos experimentos, como para el caso de los modelos individuales, KNN y Lasso CV mostraron un excelente rendimiento predictivo. Hubiera sido necesario disponer de más datos para aprovechar otros modelos, ya que SVR, CART y Boosting necesitan una cantidad suficiente de datos de aprendizaje para asegurar un cierto nivel de generalización y rendimiento.

Finalmente, hemos seleccionado cuatro países europeos como ejemplos para estimar el ciclo de vida del producto MicroLED, con el fin de ilustrar algunas aplicaciones de estos modelos. También mostramos que la propuesta de predicción realizada supera a la tradicional. Posteriormente, hemos comparado los resultados de varias predicciones MLR. Las apariencias predictivas muestran que a mediados de 2028 puede producirse un despegue de la demanda, a principios de 2031 puede llegarse a un máximo y muestran finales de 2033 como acumulación. El mejor modelo de conjunto (Bosque Aleatorio o Random Forest por su denominación inglesa) predice dichos puntos ligeramente antes (2024 como despegue, principios de 2026 como pico y finales de 2029 como acumulación). El método de Aprendizaje Profundo (Deep Learning por su denominación anglosajona) predice el ciclo de vida más rápido de MicroLED ya que la demanda comienza a aumentar significativamente en 2.4 años, es decir, a mediados de 2024. Se espera que el mercado principal alcance en 2025 un pedido máximo de aproximadamente 8,9 millones de televisores MicroLED. Asimismo, se espera que el período de saturación ocurra más adelante en 2027. La estimación de los coeficientes de innovación, p, e imitación, q, usando un método de analogía (Look-like) muestra una precisión de predicción similar o menor que KNN y Lasso CV, disponiendo de una predicción más moderada con los modelos de regresión simple. El proceso Look-like produce aproximadamente el doble de error que el mejor modelo de regresión multilineal entre los modelos de regresión individuales. El error de predicción es aproximadamente diez veces mayor que el modelo de regresión del mejor conjunto, Random Forest. Este hecho muestra de forma indirecta que podemos tener confianza en el marco de estimación de los parámetros del modelo utilizando Random Forest.

En definitiva, creemos que este trabajo contribuye a una predicción previa al lanzamiento al mejorar la construcción de la base de datos del producto y proponer un nuevo enfoque que utiliza regresión estadística y algoritmos de aprendizaje automático de última generación. El uso adecuado de la regresión estadística y los algoritmos de aprendizaje automático pueden mapear con bastante confianza la relación entre los atributos de los productos existentes y las características de difusión, y permiten predecir de una forma adecuada la demanda de nuevos productos.

Entre las extensiones podríamos citar: a) Se podría mejorar el rendimiento de los modelos predictivos al adquirir datos de demanda para un mayor número de productos con el fin de construir una base de datos de productos adecuada. Como antecedentes encontramos que un algoritmo altamente sofisticado con alto poder predictivo en el aprendizaje automático muestra un rendimiento relativamente bajo. Por ejemplo, los árboles de regresión y la regresión de vectores de soporte requieren datos de aprendizaje suficientes para garantizar el rendimiento de la generalización. El número total de productos utilizados en este documento es 174, lo que significa que los registros pueden no dar un ajuste óptimo para algunas operaciones de los algoritmos. Creemos que la llegada del mundo de Big Data y los datos de PoS fácilmente disponibles por parte del sector público / privado introducirán un gran potencial de mejora. b) Por lo general, se puede mejorar el rendimiento de los modelos incrementando los atributos del producto en la base de datos. Aunque ya utilizamos 23 variables en este trabajo, es posible que no sean suficientes para explicar las características específicas de la difusión de diferentes productos. Por lo tanto, es necesario revisarlos y actualizarlos. Por ejemplo, las variables esenciales relacionadas con países o industrias particulares podrían ayudar. Además, estudios exploratorios adicionales podrían permitir la identificación de factores específicos del contexto que afectan la distribución del producto. c) Podemos mejorar los procesos de estimación para el tamaño del mercado. En el trabajo extrapolamos el coeficiente m utilizando números de hogares de las estadísticas de la OCDE por país y la demanda latente por hogar. Aunque los coeficientes de innovación e imitación son suficientes para predecir la curva del ciclo de vida del producto, se necesita información sobre el tamaño potencial del mercado para hacer una previsión de la demanda más precisa. Dado que el posible tamaño del mercado es sensible a factores microeconómicos y macroeconómicos como los niveles de ingresos, las regulaciones y las culturas de los países de lanzamiento, estos efectos resultan difíciles de estimar. Aunque existen numerosas formas de evaluar el tamaño potencial del mercado en la literatura, nuestro trabajo utiliza los 11 algoritmos posibles para estimar solo los coeficientes de innovación e imitación, no el tamaño potencial del mercado. Aunque únicamente usamos el número de hogares, un pronóstico de demanda más preciso requiere pronosticar el posible tamaño del mercado a través de otros métodos como enfoques centrados en las preferencias del cliente, principalmente utilizando cuestionarios de clientes.

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CAPÍTULO 2: Analysis of the determinants of Korean and Japanese FDI outflow to Europe

Abstract

Korean and Japanese companies are increasing FDI (Foreign Direct Investment) in Europe and opening subsidiaries and plants in the EU, as descriptive statistics show. Our aim in this chapter is, first, to perform a panel analysis of Korean FDI inflow. Secondly, we do a panel analysis of Japanese FDI inflow. For both countries, we discard a fixed-effects model versus a random-effects model employing Hausman tests. In a simple regression of FDI to its determinants, we find some important factors contributing to both positive statistical significance. Thirdly, we perform the quasi-experiment to see the counterfactual impact of Japanese FDI with the EU. Over many combinations of determinants, corporate tax and labor productivity show good explanatory power in a simple panel data regression model. Then, we run DID analysis to show the Korean-EU FTA (Free Trade Agreement) impact on Korean FDI. We find a potential impact of the FTA to increase FDI by 317%, while the potential impact of the Japan FTA inflow is 732% additional to current levels. The results support several important implications for the impulse of bilateral relationships among the EU and other countries.

Keywords

FDI, Difference in Difference, economic analysis, Korean-EU FTA, Japan-EU FTA, Fixed effects, random effect

JEL Codes

C31, C33, E17, E27, F16, F21, F23, F37

1. Introduction

Along with international trade, Foreign Direct Investment (FDI) has been considered a motor of economic growth and one of the world's most defining sectors globally in the past two decades. At the aggregate level, this type of private capital flows has grown at an unprecedented rate. From 1980 until now, FDI in the world has grown at a remarkable rate. Moreover, FDI is growing even faster than international trade, the national connection economy (World Investment Report). In fact, over the past decades, the growth rate of world FDI has exceeded the growth rates of both world trade and Gross Domestic Product–GDP- (UNCTAD, 2001). During the fluctuations of capital flows in the 1990s, FDI was the primary source of flows to developing countries.

Contrary to other capital flows, FDI is less volatile and does not show a pro-cyclical behavior. Therefore, it has become the "favorite capital inflow" for most developing countries. In the second half of the 1990s, FDI flow grew annually by nearly 32%. Compared to the 1.5% annual growth in exports and the 0.6% yearly increase in GDP, it is not surprising that the 90s have seen the development of formal economic models of multinational enterprises (MNEs) and increased empirical research about the factors driving FDI patterns. Continuing the growth, in the 2000s, according to (Eurostat Yearbook, 2007), world FDI inflows increased by 9% in 2005. Although this tendency experienced a significant change during the last financial and economic crisis, Global FDI falling from 2007 to 2008 at a 14% rate, the trend turned again during the global economic recovery from 2009 to 2011. Therefore, many countries implemented policies to promote FDI inflows, including China, which was previously closed to foreign investment countries, have recognized the economic benefits of foreign investment, and have opened their borders to foreign capital. Global FDI flows exceeded the pre-crisis average in 2011, reaching $1.5 trillion despite the global economy's turmoil. However, they remained in 2012-2014, some 23% below their 2007 peak. After the 2012 slump (Global FDI fell by 18% to $1.35 trillion in 2012), global FDI returned to growth, with inflows rising 9% in 2013 to $1.45 trillion In 2014. The recovery seems to take longer than many experts expected because of global economic fragility and policy uncertainty (UNCTAD, 2012-2015). However, investments by MNEs are now reaching a record again: developed countries and developing Asia now invest abroad more than any other region. Nine of the 20 largest investors were from developing or transition economies. These MNEs continued acquiring developed-country foreign affiliates in the developing world.

In this ever-challenging economic environment, regardless of their level of development, geographical location, or industrial structure, economic policies to attract FDI from MNEs, have become standard in most countries. One of the most critical policy questions is: "What policy-makers should attract inward FDI or What is a golden rule to attract FDI in general"? This question wonders about the policy variables used to attract FDI. Here, in the short run, governments' policymakers can directly influence policy variables, and they will be crucial determinants of FDI. However, the more valid question, in the long run, would be: "What are the country-specific factors in certain countries in a certain period"? There were many trials and errors to define the golden rule variables to attract inflow FDI. Still, none of them tend to be consistent in various contexts, as we discuss later. In this sense, it is necessary to specify the context such as partner country, industry, and other socio-economic variables to customize an appropriate policy to the context after finding an FDI relevant policy variable. Our paper delves into the FDI relationship between Korea, Japan, and the EU countries to focus on the importance mentioned below and find some possible implications of policy changes.

South Korea is no longer just a recipient of FDI. It is also emerging, steadily and rapidly, as a source. South Korean companies stepped up their outward FDI in the middle of the 1980s, and these investments continued to increase. Basically, between 1999 and 2003, the total number of new foreign affiliates was 10,448, with the total amount of FDI standing at 20 billion dollars. Despite the increasing trend of FDI outflows, especially in Europe, the main determinants of FDI location decisions for the South Korean multinationals have not been well studied yet.

There have been some papers that show increasing tendencies of South Korean FDI inflow to the EU. According to (Hwang, et al., 2007), the FDI of Korean firms in the EU has increased dramatically since the late 1980s and early 1990s. This increase in investment activity gave rise to a debate on existing FDI theories' ability to fully explain Korean FDI types and motivations in the developed economies (e.g., the EU). Dent and (Randerson and Dent, 1996) examines Korean FDI forces in the EU and states many qualitative factors such as reactionary motives confronted by policy threats. It also underpins the importance of large chaebol (conglomerate) companies. Significant fluctuations in Korean Investment abroad support this argument.

EU28 FDI flows into South Korea rose from $1.2 billion in 2010 to $2.5 billion in 2011 and 2012, while South Korean FDI to the EU27 increased from $1.6 billion in 2010 to 3.9 billion in 2011 and then fell to $1.4 billion in 2012, still being significant increase and in 2017 and 2018 they are breaking surpassing $5 billion every year. Meanwhile, EU-South Korean "Trade in service" and "Trade in good" continuously increased between 2008 and 2015. Not explaining fluctuations not related to the standard macroeconomic indicator, we might have to resort to the 'chaebol' theory that negative perspective about the European debt crisis in 2011 might influence senior managements' decision about an investment.

Table 1. EU28 FDI Flow with Korea

	2010	2011	2012	2013	2014	2015	2016	2017	2018
EU28 FDI in South Korea	1,778	2,497	2,455	2,225	-2,593	-24	2,380	5,871	3,544
South Korean FDI in the EU28	1,648	3,948	1,376	4,348	614	2,120	1,808	5,870	9,710

Unit: $ Million
Source: OCED stat

The EU-South Korea Free Trade Agreement (FTA) entered into force in July 2011. It goes further than any previous agreement in lifting trade barriers, and it was the EU's first significant trade deal with an Asian country (even called 'a new generation of FTAs'). The agreement eliminates duties on industrial and agricultural goods in a progressive, step-by-step approach. The EU-South Korea FTA already removed much of the import duties when the FTA entered into force on 1 July 2011 before eliminating almost all duties from 1 July 2016. The FTA also addresses non-tariff barriers for the service sector. This change opens new opportunities and challenges for both sides since it grants market access in services and investments, including provisions in government procurement and intellectual property rights (IPR).

As for Japan, FDI is relatively closed to a foreign investment like Korean FDI but more extreme. The 2001-2015 average of Japan's inflow FDI/GDP ratio is slightly higher than that of South Korea with 1.66%, and inflow is incredibly low with 0.18% for outflow (South Korea's FDI/GDP ratio is 1.64% for outflow, 0.98% for inflow). This average compares to an EU 2001-2015 average of 6.04% outflow, 7.59% inflow FDI/GDP ratios. Some EU member states such as Ireland, Luxembourg, and the Netherlands, have FDI/GDP ratios of over 20%. The result means the immense potential for South Korea and Japan's growth if policymakers in these countries take on the right decisions. While EU investment in Japan is steady, Japanese direct investments in Europe are rapidly increasing by about €10 billion per year, and amount to about €160 billion, almost twice as high as European investments in Japan. Therefore, more attractive for Japanese direct investments in the opposite direction (Table 1). As (Randerson & Dent, 1996) and other authors suggest, Korea and Japan show similar FDI patterns to other countries, reacting to change in institutional, country-specific factors, and micro and macroeconomic situations. On top of that, senior management's future perspective about the target, the country is not negligible since conglomerates' roles in the economy are huge in both countries. For 2014, Top ten conglomerates' production accounts for 28% of Japan's GDP and 48% of Korea's (World bank, Korean financial supervisory service).

(Randerson & Dent, 1996) stated that South Korea's rise to modern industrial statehood and becoming Asia's third-largest economy has led to inevitable comparisons with Japan. The compare significant investments from Japanese Zaibatsu conglomerates' investment witnessed from the early 1980s onwards with Korean the large chaebol conglomerates their investments in the 1990s.

As shown in Table 2, the Japanese total Inward FDI stock to the EU is still five times bigger than South Korean FDI due to a long history of investment. However, due to the increasing importance of cooperation between EU and South Korea, thanks to FTA and economic growth, understanding the factors, especially driving Korean Investment for the EU policymaker who has experience with other Asian investment, is getting more and more important

Table 2. Foreign direct investment 2014, € billions (European Commission)

Country	Inward stocks	Outward stocks	Balance
Korea	20.3	43.7	23.5
Japan	160.5	78.9	-81.6

After Korea's economy boomed in the 1990s, Koreans and Japanese invested outwards with quite similar patterns until the 2007-2008 financial crisis. Many papers, including (Randerson & Dent, 1996), compare Korea with Japan in the economics literature. They show many similarities in the industry (i.e., high-tech industries, electronics, shipbuilding, car industry, and other related industries.), strength and weakness, conglomerates (Zaibatsu and Chaebol), culture, geography. The consequence can lead us to the conclusion that the FDI flows will also show similar patterns. Then, is this deduction accurate?

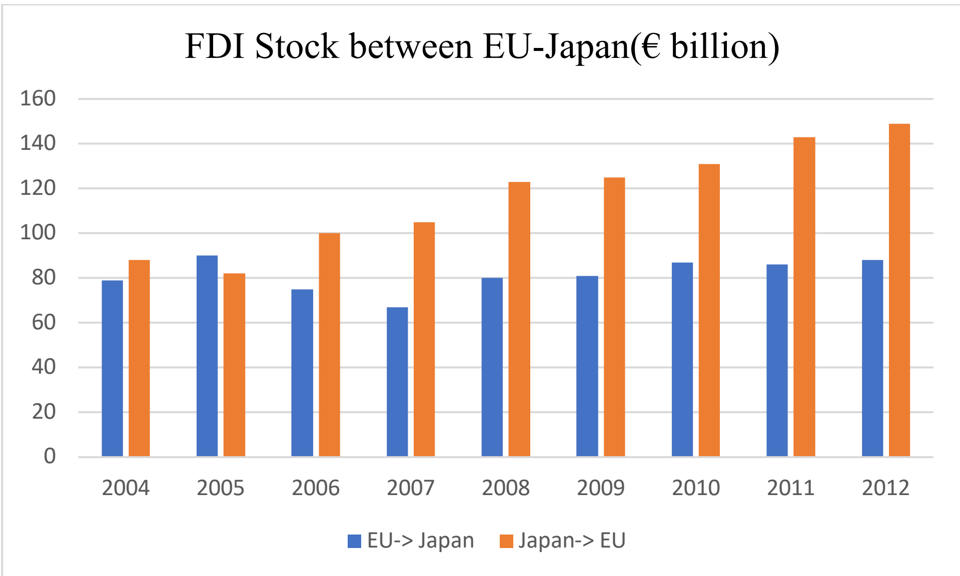

Figure 1 JAPAN-EU FDI stock between EU27 and Japan (Team Eurotechnology Japan)

Starting from the state facts so far and questions, in this paper, using statistics from various sources (mainly Eurostat, OECD, and UN), we focus on Korean FDI inflow to the EU to answer fundamental questions like What determines where Korean and Japanese FDI goes in? Are these inflows different from each other? Which are their similarities? Which policy measures trying to incentive FDI from Japan or South Korea to the EU must policy-makers propose? Moreover, we like to test the impact of FTA on Korean FDI inflow to Europe using the same model to predict Japanese FTA's only influence.

So far, we have described the status and perspective of the FTA and FDI situation in South Korea and Japan. We now deep into this study's primary objective is to study the determinants of the EU's direct investment from the two countries and identify similarities and dissimilarities between them. In contrast to many existing studies using inflows, this paper looks at both EU groupings together. In a gravity context, we use fixed and random effects panel data models to cover these aims. A dataset on annual FDI flows between 27 EU member states, and we obtained some more data of nine main extra-EU investing partners from the Eurostat and World Bank databases and merged them. We explain both this information and the variables used below.

The paper is structured as follows: firstly, we give a short empirical overview and revise the existing literature on the EU's investment conditions. Secondly, we discuss and define the primary survey's theoretical premises and the model framework's econometric fundamentals. Finally, we present and discuss the empirical results. The paper ends up with a summary of the main conclusions.

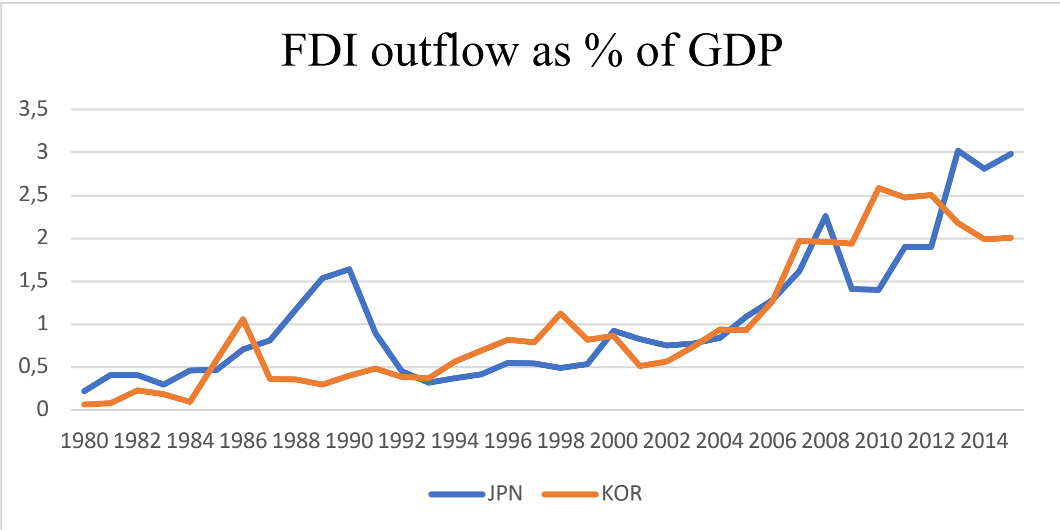

Figure 2 FDI outflow ratio (World Bank)

2. Literature review

To analyze the factors attracting FDI, we start in Table 3 (Nunnenkamp, 2001) (Nunnenkamp, 2002). He investigates the importance of spatial interaction impacts (based on regional group dummies), persistence in the levels of FDI across industries (using AR (1) time series models), policy incentives in addition to the conventional factors like market size, production costs, and infrastructure as determinants of FDI locational choices. We summarize the potential determinants of FDI in Table 3 grouped by country, institutional, economic, and sectoral indicators.

Table 3. Potential factors affecting FDI (Nunnenkamp, 2001 and 2002)

Indicator category	Indicator
Country indicators	Market size
	The level of Openness
	Infrastructure
	Distance with the home country
	Regional market link
	Natural resources

Institution indicators	Law and social norms
	Regulation enforcement
	FDI incentives related policies
	Education and human capitals
	Political stability
Economic indicators	Labor costs and productivity
	Macroeconomic stability
	Economic growth rate
	Level technology
	Balance of payments
	Inflation
Sector indicators	Scale industrial sectors
	Competitiveness

Of course, we use standardized FDIs as a dependent variable like many other studies. Despite the increasing trend of FDI outflows, especially in Europe, the main determinants of FDI location decisions for the South Korean and Japanese multinationals have not been well studied yet. There have been some papers that show increasing tendencies of South Korean FDI inflow to the EU. According to (Hwang, et al., 2007), the FDI of Korean firms in the EU has dramatically increased since the late 1980s and early 1990s. This increase in investment activity gave rise to a debate on existing FDI theories' ability to fully explain Korean FDI types and motivations in the developed economies (e.g., the EU). Japan is a significant economic partner for the EU. Japan is the world's third-largest national economy, accounting for 2% of the world population and around one-eighth of world GDP. The EU and Japan together account for close to 40% of global GDP, their bilateral trade being around €145 billion per year. Historically, we can characterize Europe and Japan's trade trend by a substantial trade surplus in Japan's favor. Although surplus figures have gotten small recently, the EU and Japan business relationship remains challenging due to individual structural differences in the society and economy. (Head & Mayer.,2004) develop a theoretical model of location choice under imperfect competition to formalize the notion that firms prefer to locate their investments. However, due to specific structural differences in the society and economy between the EU and Japan, doing business remains challenging.

Papers studying the determinants of Korean and Japanese FDI are scarce. They mostly focus on inflow FDI to Korea and Japan- Investments realized in Korea and Japan by foreigners, to help them get over structural and cultural differences. Because since the 1990s, Korea and Japan started to increase FDI starting from China, many papers deal with determinants and tendencies of Korean and Japanese investments in other countries. (Kang, et al., 2007) use extensive and unique firm-level data for South Korean foreign affiliates in China and investigates the determinants of South Korean multinational companies' location choice. Using conditional logit models, they found some important factors playing a positive role in deciding the location, namely, market size, government policies, quality of labor, and transport infrastructure. They also find some adverse and significant factors like labor costs, inner waterways, and distance. They use the conditional logit estimation method proposed by (McFadden, 1974), which is similar to that used by (Head, et al., 1995) for their study of Japanese manufacturing investments in the United States (aggregated data of FDI flows and OLS have dominated in existing studies on the location patterns of FDI). However, the aggregated data and methodology contradict the disaggregated and discrete nature of FDI(Cheng & Stough., 2006). In the absence of relevant firm-level data to use, we rely on regional level data found in Eurostat and OECD stats. We try to identify whether South Korean/Japanese FDI responded to policy initiatives such as special economic zones and whether other factors drove the location decision.

3. A set-up proposal

In this paper, we follow (Driffield, 2002), who models the probability of a firm entering or expanding into an EU country, fundamentally driven by its expected future profits (Π^c). Given a lifetime of the investment of T-periods and the discount rate, r, we can write:

$$Prob.(FDI) = \phi_1 \left[\sum_{p=0}^{T} \left(\frac{r}{\mathrm{r+1}}\right)^p \Pi_{t+p}^c\right] \quad \textbf{(1)}$$

In practice, this probability is unobservable. Instead, we can re-write it, following Driffield (2002), as a function of country characteristics :

$$\sum_{p=0}^{T} \left(\frac{r}{\mathrm{r+1}}\right)^p \Pi_{t+p}^c \quad = \phi_2(X_{1i}, X_{2i}) \quad \textbf{(2)}$$

X_{1i} are variables thought to be positively related to profits, and X_{2i} is a set of variables postulated to reduce the expected profitability. We follow the extensive literature and identify the following variables: market size, openness, infrastructure, market growth (or growth in the gross domestic product -GDP- per capita), sound monetary and fiscal policies, financial depth, agglomeration advantages, and access to natural resources. Usually, all these variables are highly correlated and, therefore, it is an empirical question if we can use jointly in the regression analysis. However, the X_{2i} are variables that are negatively related to expected profits. Concerning them, we can identify risk, high domestic investment (postulated to deter new entry), high industry concentration, and increased economies of scale (Rodrik, 1991). Besides, we also find high political risk and lack of good as hurting FDI (Jenkins & Thomas, 2002).

3.1. Estimation methods

By aggregating individual decisions, we can derive from equations (1)-(2) a basic to the determinants of FDI into EU, which we write as:

$$y_{it} = \alpha_i + x_{it}\beta + \epsilon_{\mathrm{it}} \quad \textbf{(3)}$$

i = 1, …, N and t = 1 …, T and where y_{it} = *FDI inflow/GDP* for the invested country i in period t; x_{it} is a whole vector of explanatory variables; α_i is a country-specific intercept, ε_{it} is the error term. The availability of panel data allows us to estimate (3) taking advantage of this data structure. We can justify using a panel approach both because the restrictions $\alpha_i = \alpha_j = ... = \alpha$, do not hold, and because panel data allows us to estimate parameters take account of these parameters proxying some non-time varying unobserved specific effects. Moreover, the use of panel data leads to estimates that are, at least, more efficient. If we add time effects to (3), we have

$$y_{it} = \alpha_i + \alpha_t + x_{it}\beta_t + \epsilon_{\mathrm{it}} \quad \textbf{(4)}$$

Where α_t is a time-specific intercept. When only cross-section data is available, we cannot identify α_i. When only time-series information is available, we cannot identify α_t. So, the panel structure allows the identification of both effects. Let us assume for the moment that the x_{it} are weakly exogenous variables (in the sense that they are uncorrelated with the mixed error ϵ_{it}). We also think that the relationship is static, i.e., x_{it} does not contain lags of y_{it}. The advantage of being able to control non-time varying unobserved specific effects, α_i, could be a fundamental problem for adjusting $y_{it} = \alpha_i + \alpha_t + x_{it}\beta_t + \epsilon_{\mathrm{it}}$. They correspond in this context to country-specific latent variables.

Let us define $\alpha = E(\alpha_i)$, so $E(\alpha_i - \alpha) = 0$. Our model $y_{it} = \alpha_i + \alpha_t + x_{it}\beta_t + \epsilon_{\mathrm{it}}$ may be written

$$
\begin{aligned}
y_{it} &= \alpha_i + \alpha_t + x_{it}\beta + \epsilon_{\mathrm{it}} \\
&= \alpha_i + \alpha_t + x_{it}\beta + (\alpha_{\mathrm{i}} - \alpha + \epsilon_{\mathrm{it}}) \\
&= \alpha_i + \alpha_t + x_{it}\beta + \eta_{it}
\end{aligned}
\quad \textbf{(5)}
$$

We note that under the assumption $E(\alpha_i - \alpha) = 0$, $E(\eta_{it}) = 0$. One way of understanding this "data generating process" is this: we first draw, α_i from the set of n fixed values or randomly. Next, we draw x from $f_X(z|\alpha_i)$. In both cases, one important point is that the distribution of x may vary depending on the realization, α_i. Thus, if we assume that the effects are random, there may be a correlation between α_i and x_{it}, and if so, OLS leads to inconsistent estimates. However, if the distribution of x_{it} is constant concerning the realization of $\alpha_{i,}$ x_{it} and η_{it} may be uncorrelated, although it is implausible for most of the datasets. In the case of the absence of correlation, OLS provides consistent estimates. The cases just described corresponding to any of the two alternative situations: **Fixed effects**: we assume that the different unobserved effects correspond to country dummies; **Random effects**: we assume each α_i corresponds to a random distribution variable with some properties to be specified. To get consistent estimates in this second case, we need $E(x_{it}\alpha_i) = 0$.

3.2. Standard methods for estimating the model

Few empirical papers study the determinants of South Korean FDI flows into the EU, and recent contributions have taken the form of mainly single equation OLS cross-country regression models. It is useful for comparative purposes to repeat this exercise of estimating a "standard" single-period-averaged cross-country regression of the determinants of FDI flows. However, we recognize that this approach has several limitations. Therefore, we suggest several changes to the existing literature. The limit of using OLS to estimate a single period- averaged cross-country regression results in inconsistent estimates since it may not consider the endogeneity of some of the regressors. It may suffer from omitted variable bias (if the unobserved effects are relevant for explaining FDI flows).

3.2.1. Pooled OLS estimator

The pooled OLS estimator uses the total variation to adjust the parameters. The pooled OLS estimator is obtained by stacking the data over i and t into one long regression with N*T observations and estimating it by OLS:

$$
\mathrm{y_{it}} = \alpha_i + \alpha_t + x_{it}\beta + (\alpha_{\mathrm{i}} - \alpha + \epsilon_{\mathrm{it}}) \quad \textbf{(6)}
$$

If the correct model is the pooled model and the regressors are uncorrelated with the error terms, the pooled OLS regressor provides consistent estimates. If assumption $E(\alpha_i - \alpha) = 0$ is not satisfied, the pooled OLS estimates are inconsistent.

3.2.2. Fixed effects estimator

We assume that each country has a country-specific intercept α_i, and we are the case of the fixed-effects model.[1] OLS of this model would provide inconsistent estimates of the parameters. Since N is usually large, we can estimate the model without calculating the α_i, but to do so, we have to transform the model ("within" transformation). Let us define:

$$
\bar{\mathrm{x}}_{\mathrm{i}} = \frac{1}{\mathrm{T}}\sum_{t=1}^{T} x_{it}
$$

[1] First here, we will assume that the model does not contain time effects for simplicity of notation.

$$\bar{\epsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \epsilon_{it}$$
$$\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it} = \alpha_i + \frac{1}{T}\sum_{t=1}^{T} x_{it}\,\beta + \frac{1}{T}\sum_{t=1}^{T} \epsilon_{it}$$
$$\bar{y}_i = \alpha_i + \bar{x}_i\beta + \bar{\epsilon}_t \qquad \textbf{(7)}$$

The transformed model is:

$$y_{it} - \bar{y}_i = \alpha_i + x_{it}\beta + \epsilon_{it} - \alpha_i - \bar{x}_i\beta - \bar{\epsilon}_t$$
$$y^*_{it} = x^*_{it}\beta + \epsilon^*_{it} \qquad \textbf{(8)}$$

where $x^*_{it} = x_{it} - \bar{x}_i$ and $\epsilon^*_{it} = \epsilon_{it} - \bar{\epsilon}_i$. In this model, we need x^*_{it} and ϵ^*_{it} to be uncorrelated, apply OLS, and obtain consistent parameter estimates of β, even if $E(x_{it}\alpha_i) \neq 0$, because the transformation used has ruled out the unobserved effects.

3.2.3. Random-effects estimator

For the original model (6), we assume α_i comes from a distribution with $E(\alpha_i) = 0$ and $E(x_{it}\alpha_i) = 0$. Then, OLS gives consistent (although not efficient) estimates. We should note that if the composite error $\alpha_i + \eta_{it}$ is correlated (i.e., there is a correlation through α_i for the same individual unit at different periods), we should use GLS to get efficient estimates of the parameters. With fixed effects models, we do not estimate the effects of country invested variables not changing across by controlling for them. These facts mean in our context, Korean or Japanese FDI patterns to specific EU countries are similar and assumed to be more or less the same across countries like "random assignment." However, Random effects models will estimate each country's effects, not controlling for omitted variables; therefore, the estimates may be biased.

3.2.4. Difference-in-Differences (DID)

A suitable method to estimate the causal effects of an intervention is DID. Our interest in using DID is due to the following set-up. While Korea signed an FTA with the EU during the period of our sample, Japan did not. So, we have 27 EU destinations of Korean and Japanese FDI during 2003-2014, and there are two differentiated periods. The first period is from 2003 to 2011 without any FTA in any of the two countries. The second is from 2012 to 2014 when a policy measure has affected the Korean inflows to EU countries while Japanese inflows could have benefited from signing an agreement, although the EU did not implement new policies toward Japanese firms. We can see this as a quasi-experiment to estimate the causal effects of introducing an FTA. Korean firms got the treatment at the time of the Korea-EU FTA, while Japanese firms did not. Therefore, we can estimate the agreement's causal effect if we can assume the counterfactual that Japanese firms would behave as the Korean firms if the EU and Japan had signed the FTA in 2011.

The DID estimate uses four data points to control the potential impact of other events developed in Korea and Japan, different from the EU FTA, correlated to the evolution of FDI. Our interest is to estimate the effect of the EU FTA if Japan had signed it in 2011. The quasi-experiment construction entails that both the treatment and control groups have similar characteristics in firms' behavior concerning FDI (assumption of common trends). DID is used in observational settings without assuming the exchangeability between the treatment and control groups. It relies on a less strict exchangeability assumption, i.e., in the absence of treatment, the unobserved differences between treatment groups and control groups are the same over time.

Figure 3 presents how DID operates in our context. The four data points represent each group's observed mean (average in two different periods for the two countries), and we find the information required to calculate the causal effect of the treatment. The dotted lines represent the evolution of FDI without the treatment in Korea (not observed by the researcher since their firms experienced it in 2011) and the development of FDI with Japan's treatment (not monitored by the researcher since Japan did not sign the FTA). Note that although the means are different, they both have the same time trend (i.e., slope). The critical hypothesis for any DID strategy is that the treatment and control group (in our case Japanese FDI) would follow the same trend in the absence of the treatment. This result does not mean that they should have the same average impact. The common trends assumption is difficult to verify, but if we get similar panel analysis results and unify the variables to make a model, this assumption makes sense since we can control unobserved factors potentially violating the maintained hypothesis. However, even if the previous trends are the same, we still have to worry about other policies changing at the same time and affecting the estimation of the causal effect.

We would rely on our results whenever firms in Korea and Japan behave similarly. Many other indicators and studies suggest that South Korea is following Japan's economic way somehow. The Korean and Japanese economy, closely related to trade and investments, show very similar patterns as neighboring countries. In particular, both countries' economies grow and decline rapidly with repeating histories and are affected in the same way by the rest of the world economy. Therefore, we would believe that the counterfactual will be well defined since their firms will behave similarly concerning FDI. We can see this DID approach as a particular case of the fixed effects estimation. In our case, we can state our generated quasi-experiment as follows. We observe FDI inflow to the EU from Korea before and after the treatment (introducing the FTA in 2011). We also monitor Japan's FDI inflow to the EU both before and after 2011, but Japan did not sign an FTA with the EU. Then, our question is, what would happen if Japan and the EU had signed an FTA in 2011? And we use the Korea-EU FTA to answer this question since both countries are similar in their firms' behavior concerning FDI decisions in EU countries.

We can derive the specification from estimating the causal effects from equations (3) and (4). by assuming that the model does not contain time effects except for the EU-Korean FTA, and only fixed-effects for the simplicity, the determinants of Korean and Japanese FDI and into EU countries, which we write as:

$$y_{cit} = \alpha_{ci} + \alpha_t + x_{cit}\beta_c + T_{it}\gamma + \epsilon_{cit} \qquad \textbf{(9)}$$

Where c represents the country (Korea or Japan), i refers to the destination country of FDI, and t is the period. T refers to the treatment, so it takes value if c = K and t > 2011. So, y_{Kit} and y_{Jit} are Korean/Japanese *FDI inflow/GDP* to destination i in the period t; namely, using Figure 3, y_{Kif} is Korean FDI inflow to EU at county i at the time, f=0 and 1, y_{Jif} is Japanese FDI inflow to EU at county i. Moreover, x_{cit} consists of FDI vectors of explanatory variables to the destination i at time t for the whole country c. And, of course, α_{ci} is a country-specific intercept. Finally, T_{it}, the treatment consists of the interaction between a dummy taking value 1 for Korea and a time dummy taking value 1 after 2011 when the EU-Korean FTA was introduced.

Figure 3 Difference in Differences in our model

As described in the data section below, we combine databases of Eurostat, UNStat, and others for the year 2003-2014 (see Appendix B). The estimation of (9) provides the policy's causal effect, resulting from two differences, one in time and another across the two countries, Korea and Japan. In other words, we can express the for equations for the two countries and two periods (without destination subscripts and the standard errors) in a way such that the double difference in time and across countries provides an estimate of the causal effect of the FTA (γ).:

$$y_{J0} = \alpha_J + \alpha_0 + x_{J0}\beta_J \qquad \textbf{(11)}$$
$$y_{J1} = \alpha_J + \alpha_1 + x_{J1}\beta_J \qquad \textbf{(12)}$$
$$y_{K0} = \alpha_K + \alpha_0 + x_{K0}\beta_K \qquad \textbf{(13)}$$
$$y_{K1} = \alpha_K + \alpha_1 + x_{K1}\beta_K + \gamma \qquad \textbf{(14)}$$

In this way, although we do not observe the FTA impact after 2011 in Japan, we can derive its causal effect under the previous assumptions.

3.3. Tests among the different methods

When panel data is available, the estimation method gets more complicated. We would like to know if considering the data's structure (which requires either within-groups or GLS) adds to OLS's pure estimation. For testing the assumption $\alpha = E(\alpha_i)$ or that there is a common intercept, we can use the Breusch-Pagan Lagrange Multiplier test. This method is a test for the random-effects model based on the OLS residual. If the test's value is significant, we reject the pooled model. Another maintained assumption to test is $E(x_{it}\alpha_i) = 0$. When it holds, OLS and within-groups provide consistent parameter estimates, but if α_i is considered random, only GLS provides efficient estimates.

We will use a Hausman test to discriminate between fixed and random effects models. This test is equivalent to testing for the absence of a correlation between the unobserved effects and the regressors. We compute the test using the difference between GLS and within estimates. We can also use OLS since they also provide consistent estimates. If we reject the null, we can conclude that the heterogeneous effects and the regressors are correlated, so we should use the within-estimator to transform the model and rule out the unobserved effects. In case the test fails to reject the null, results, and variables are not correlated. However, the null hypothesis could still not be correct in the presence of misspecification.

3.4. Data

We get the data used in this chapter from Eurostat for the EU-FDI inflow data for Japan and Korea. On the other hand, we take the rest of the variables from the World Bank statistics. Table 4 shows the variables used attending the classification following (Nunnenkamp, 2001 and 2002) and some alternatives. We have T = 12 (2003-2014) and N = 54 (27 destinations to EU countries and two origins in Korea and Japan).

Table 4. Summary of variables per indicator category

Indicator category	Indicator	Variants1	Variants2
Country indicators	Market size	GDP	
	The level of Openness	OPENNESS	
	Infrastructure	QUAL_INF	
	Geographic, distance with the home country	4 Regions	
	Regional market link	GDP_EURO_PPP	EURO
	Natural resources	N/A	
Institution indicators	Law and social norms	EASE_BIZ	
	Regulation enforcement	Time_Paper	
	FDI incentives related policies	Corporate_Tax	VAT
	Education and human capitals	SCHO_SEC	LABOR_PROD
	Political stability	N/A	
Economic indicators	Labor costs and productivity	LPI	Labor_COST
	Macroeconomic stability	INCOME_GINI	
	Economic growth rate	GDP_GROWTH	
	Level technology	HighTEC_EXPORT	
	Balance of payments	ACC_BAL	
	Inflation	INF	
Sector indicators	Scale industrial sectors	N/A	
	Competitiveness	N/A	
	Level of subsidy for domestic sectors	N/A	

The details of definitions (and denomination) are found in appendix a.

4. Empirical Analysis

4.1 Pooled OLS estimator

As briefly mentioned, the advantage of using OLS is its simplicity, but it could provide biased estimates when there is country heterogeneity. Breusch-Pagan tests for all models reject OLS because of the presence of country-specific differences (Breusch-Pagan LM test value= 74.65). In our exercise, T is relatively small compared to N, but we do not think it creates problems either for pooled OLS or fixed-effects models, except for OLS in the presence of correlated effects. We should also note that many indicators have similarities and differences that we need to address while conducting the modeling. i.e., between variation is more important than within variation. Due to it, OLS possibly overestimates the coefficients. From 2003 through 2014, Korea had, on average, 618% more FDI inflow. Moreover, after 2011, the EU-Korean FTA year, the difference gets bigger by 377%.

The full model with 20 all coefficients shows extraordinary explanatory power($R^2 = 0.62$), and ten coefficients are statically significant at standard levels. However, it shows sometimes counter-intuitive results. For example, education and human capitals and labor productivity have negative signs, and openness and income inequality (measured by the Gini) have positive signs. Many variables positively correlate in the full model, and the regression results, if we take them all together, maybe they are unreliable by severe multicollinearity. This result calls for the extraction of underlying factors to reduce the number of political risk indicators to fewer elements.

Indicator categories, country indicators, institution indicators, and economic indicators show a strong correlation to FDI inflow to the EU; We deliver the detailed OLS regression results in Figure 4. Although not all coefficients are statistically significant, their signs show consistently intuitive signs.

OLS								
	All		Country indicators		Institution indicator		Economic Indicators	
	0.6202		0.2309		0.4773		0.2609	
FDI Flow	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|
After_2011	337.63	0.012						
Korea	617.95	0						
GDP	0.00	0.010000	1085.62	0.042				
Openness	-6.82	0.122	-3.11	0.467				
Qual_InF	140.70	0.364	1463.60	0				
GDP_EURO_PPP	0.06	0.112	0.03	0.204				
EURO	767.28	0.007	240.32	0.699				
EASE_BIZ	12.59	0.065			14.66304	0		
Time_Paper	-115.60	0			-131.8177	0		
Corporate_Tax	-72.84	0.001			-77.53788	0		
VAT	-9317.28	0.025			-16406.36	0		
Scho_Sec	-21.91	0.112			1.960973	0.879		
Laber_Prod	-56.76	0.303			39.93362	0		
LPI	651.07	0.041					3457.90	0.003
Labor_Cost	-288.13	0.005					-102.06	0.042
Income_Gini	48.59	0.111					-98.02	0.254
GDP_Grouwth	-160.98	0.875					16.72	0.467
HighTEC_EXPORT	-1.67	0.924					177.06	0
ACC_BAL	1.81	0.902					193.48	0.204
INF	-27.06	0.31					-182.4091	0.699
_Cons	2886.77	0.262	-5747.73	0	-5872.74	0	-13168.87	

Figure 4. Pooled OLS results

4.2. Fixed and Random effects estimator

Selecting between Fixed estimator vs. Random Estimator

When deciding between fixed or random effects, we run a Hausman test. The null hypothesis H_0 for this test is 'the preferred model is random effects, and under the alternative, H_1, we choose fixed effects (see Greene, 2008, chapter 9). If the Hausman test shows "significant differences" between the coefficients for the fixed effects and the random-effects model, we need to use the fixed effects model to get consistent estimates since the model's transformation rules out unobserved time-varying factors correlated with the regressor.

Korean FDI to EU countries

After Hausman tests for regression variables with coefficients per indicator categories for all models, we find that fixed effect models are preferred, except for the model with all coefficients, in which random effect models are preferred. Figure 5 reports the results. Out of country indicators, four regions (East as default, West, North, and South) are time-invariant coefficients. Therefore, the fixed effect estimation ignored them during the regression process. All in all, most of the variables show the expected signs. In the case of the average time of paperwork or labor cost, since they are strongly correlated with GDP per capita, which is one of the most defining FDI factors when using GDP, they have unexpected negative signs. However, they turn out to be positive when we eliminate GDP related variables. Other variables, except "openness" do not influence FDI. A one-point increase in openness implies a 31% FDI inflow increase. As for institution indicators, most of them show the explanatory power of FDI. Corporate tax rate (60%), VAT (21%), labor productivity easiness of opening a new business. In the case of economic indicators, only labor costs have a statistically significant impact.

	All		Country indicators		Institution indicator		Economic Indicators	
Method	Random		Fixed		Fixed		Fixed	
FDI Flow	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|
Openness	6.56	0.199	31.25	0.003				
Qual_InF	158.96	0.466	329.55	0.465				
Western	omitted	omitted	omitted	omitted				
Northern	866.58	0.055	omitted	omitted				
Southern	2026.21	0.044	omitted	omitted				
GDP_EURO_PPP	0.06	0.254	-0.10	0.17				
EURO	1101.18	0.006	241.60	0.655				
EASE_BIZ	12.53	0.221			4.30	0		
Time_Paper	-193.41	0			-124.69	0		
Corporate_Tax	-120.04	0			-60.75	0.069		
VAT	-172.56	0			-21.03	0		
Scho_Sec	6.20	0.758			7.65	0.751		
Laber_Prod	27.34	0.687			393.10	0		
LPI	307.21	0.438					-660.12	0.478
Labor_Cost	-334.48	0.007					-600.47	0
Income_Gini	-121.84	0.001					-220.76	0.118
GDP_Grouwth	-222.42	0.761					-410.26	0.862
HighTEC_EXPORT	19.63	0.388						
ACC_BAL	-6.64	0.706					72.87	0.095
INF	-31.21	0.31					123.24	0.11
_Cons	11295.98	0	-14536.29	0	-11789.69	0	-1005.32	0.856

Figure 5. Korean FDI stock inflow to the EU

Japanese FDI to EU countries

We find that random-effects are preferred approaches according to Hausman tests for all models, except for the model with all coefficients, for which we choose fixed-effects. Figure 6 presents these results. All in all, only corporate tax, paperwork time, and Balance of payment have explanatory powers, and they show expected coefficient signs. Country indicators did not have, in general, the capacity to explain FDI except for "openness", implying that a one-point increase in openness generates a 33% increase in FDI inflow. Most institution indicators show explanatory power, such as corporate tax rate (41%), VAT (33%), labor productivity, and easiness of opening a new business. The labor productivity index (367%) and labor cost have statistically significant results concerning economic indicators.

	All		Country indicators		Institution indicator		Economic Indicators	
Method	Random		Fixed		Fixed		Fixed	
FDI Flow	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|
Openness	-2.43	0.405	33.08	0.003				
Qual_InF	202.89	0.103	-348.14	0.722				
Western	omitted	omitted	omitted	omitted				
Northern	-378.16	0.143	omitted	omitted				
Southern	-294.61	0.313	omitted	omitted				
GDP_EURO_PPP	0.02	0.403	0.15	0.137				
EURO	296.00	0.197	959.00	0.655				
EASE_BIZ	-3.55	0.544			4.35	0.293		
Time_Paper	-43.05	0.018			-41.34	0.0002		
Corporate_Tax	-24.04	0.099			-33.98	0.0003		
VAT	-172.56	0.666			-485.60	0.051		
Scho_Sec	0.75	0.948			7.65	0.901		
Laber_Prod	-23.50	0.545			6.41	0.327		
LPI	-252.98	0.163					-3672.84	0.028
Labor_Cost	-109.45	0.123					-690.15	0
Income_Gini	21.53	0.308					-85.88	0.72
GDP_Grouwth	-631.61	0.383					-768.26	0.879
HighTEC_EXPORT	-3.08	0.812						
ACC_BAL	18.15	0.071					36.50	0.681
INF	26.29	0.161					47.56	0.771
_Cons	-1552.58	0.353	-4633.82	0.33	-11789.69	0	1968.71	0.834

Figure 6. Japanese FDI stock inflow to the EU

4.3. Results of the quasi-experiment

To obtain the causal effect of introducing a Korean-EU FTA, we have to decide the specification used to do the quasi-experiment. Attending tests and goodness of fit measures, we determine the specification presented in Figure 7, where we add the treatment variable to estimate the impact of FTA. The chosen model only considers corporate tax and labor productivity since it explains 79% of Korean FDI and 81 % of Japanese FDI amounts to Europe. A 1% reduction of lowering corporate tax implies a 132% increase in Korean FDI and a 362% increase in Japanese FDI. On the other hand, a 1% increase in labor productivity has a 66% and 233% impact.

occam's razor													
KOREA							JAPAN						

. * Random effects estimator							. * Random effects estimator						
. xtreg $ylist $xlist, re theta							. xtreg $ylist $xlist, re theta						
Random-effects GLS regression		Number of obs =	208				Random-effects GLS regression		Number of obs =	208			
Group variable: id		Number of groups =	26				Group variable: id		Number of groups =	26			
R-sq: within = 0.1037		Obs per group: min =	8				R-sq: within = 0.0615		Obs per group: min =	8			
between = 0.0157		avg =	8.0				between = 0.0861		avg =	8.0			
overall = 0.0187		max =	8				overall = 0.0771		max =	8			
	Wald chi2(2) =	9.38						Wald chi2(2) =	12.04				
corr(u_i, X) = 0 (assumed)		Prob > chi2 =	0.0092				corr(u_i, X) = 0 (assumed)		Prob > chi2 =	0.0024			
theta = .69986492							theta = .81044141						
-------------						----------	--------------	----------	------------	--------	---------	------------	----------
FDI_Stock	Coef.	Std. Err.	z	P>|z|	[95% Conf	Interval]	FDI_Stock	Coef.	Std. Err.	z	P>|z|	[95% Conf	Interval]
Corporate_Tax	-132.307	51.189	-2.58	0.01	-232.635	-31.9788	Corporate_Tax	-361.52	130.5025	-2.77	0.006	-617.301	-105.74
LABOR_PROD	68.6171	26.511	2.59	0.01	16.65644	120.5778	LABOR_PROD	233.082	80.88778	2.88	0.004	74.5449	391.6192
_cons	2573.699	1167.3	2.2	0.027	285.8379	4861.56	_cons	4548.315	3369.675	1.35	0.177	-2056.13	11152.76
-------------	-----------	----------	--------	---------	------------	----------	--------------	----------	------------	--------	---------	------------	----------
sigma_u	1933.9808						sigma_u	6612.058					
sigma_e	1721.1256						sigma_e	3610.534					
rho	0.55803819	(fractior	of varia	nce due t	o u_i)		rho	0.770313	(fraction	of varia	nce due t	o u_i)	

Figure 7. KOREA-Japan EU FTA panel model using corporate tax and labor productivity

The critical assumption for any DID strategy is that the treatment and control group's outcome will follow the same time trend in the experiment's absence. IF Korean and Japanese FDI inflow to the EU had the same determinants, to see the FTA impact on Korean FDI inflow to Korea. The DID regression provides the results summarized in Figure 8. Korean-EU FTA had a sole impact of increasing Korean FDI inflow to the EU by 388%. Japan-EU FTA would have an effect of increasing Japanese FDI inflow to the EU by 732M dollars.

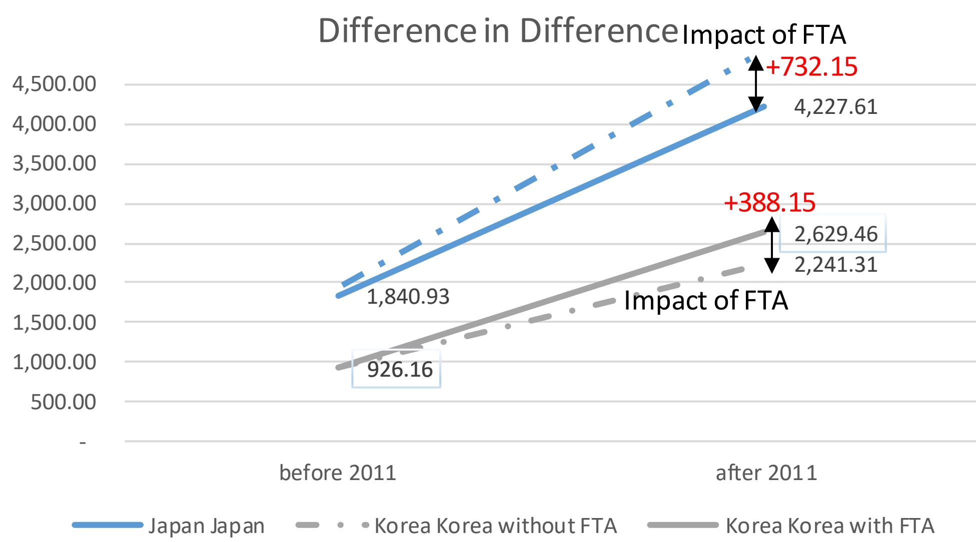

Figure 8. Graph FTA impact for Korea and forecast for Japan

5. Conclusions and comments

Statistics show that Korean and Japanese companies are increasing FDI in Europe and opening subsidiaries and plants in E.U., instead of only exporting goods produced from Korea and Japan to Europe. We use a data set on FDI downloaded from Eurostat, and we consider FDI as a dependent variable; we use a complete set of independent variables adapted from several sources such as UNstat and World Bank. We estimate several specifications of panel data models to adjust the determinants of investing through FDI. Our final specifications consider random-effects models. We tested over twenty-six countries, twenty-two independent variables.

Unlike many other kinds of literature, many independent variables (such as per capita GNP, the size of free trade zones, policy support, the wage rate, inflation rate, transportation cost/infrastructure) were significant in the US, Africa, and Europe turned out to be insignificant. The panel data OLS, random effect model, and fixed effect estimators estimate Korean and Japanese FDI determinants outflow to Europe. Across individuals and over time, many significant determinants are found and analyzed.

First, we performed a panel analysis of Korean FDI inflow. After Hausman tests random and fixed regressions with all 20 coefficients, fixed and random coefficients do not show big difference-we have a low proportion explained by the individual specific term and the rest due to idiosyncratic error. The random-effect estimator is consistent and efficient. Therefore it is our choice. We show the result of random effect regression with all coefficients s shown in Figure 5.- on the left. Many variables have statistical significance. - Since FDI inflow is a log number, it is a Log-Level Regression "if we change x by 1 (unit), we would expect our y variable to change by X%". In the random indicator regression with all variables, Time for paperwork (-193%), Corporate Tax(-120%), income inequality(-121%), and labor cost(-334%) had high negative coefficients with statistical significance. In comparison, the Euro had a very positive impact (1,101%) on FDI inflow. In the regression with country indicators, only openness had a positive coefficient (31%). In the regression with institution indicators, while Time for paperwork (-124%), Corporate Tax(-60%) and VAT(-21%) have a strong negative impacts, Labor Productivity(193%),Education(8%), Easiness of Business(4%) had positive impacts. In the regression with economic indicators, while Labor Cost (-600%) has a strong negative impact, the Balance of Payment (73%) had positive impacts. This result means that South Korean investors or many Chaebol senior managers would be strongly interested in these indicators.

Secondly, we performed a panel analysis of Japanese FDI inflow. After Hausman tests random and fixed regressions with all 20 coefficients, fixed and random coefficients do not show big difference-we have a low proportion explained by the individual specific term and the rest due to idiosyncratic error. The random effect estimator is more consistent and efficient, therefore the more preferable. We show the result of random effect regression with all coefficients in Figure 6 Japanese FDI stock inflow to E.U.- on the left. Many variables have a statistical significance-- Since FDI inflow is a log number, it is a Log-Level Regression "if we change x by 1 (unit), we would expect our y variable to change by X%".In the random indicator regression with all variables, Time for paperwork (-42%), Corporate Tax(-24%), Balance of Payment(18%) had high negative coefficients with statistical significance.

In comparison, the Euro had a very positive impact (296%) on FDI inflow. In the regression with country indicators, only openness had a positive coefficient (33%). In the regression with institution indicators, while Time for paperwork (-41%), Corporate Tax (-34%), and VAT (-485%) have a strong negative impact. In the regression with economic indicators, while Labor Cost (-3,672%) has a strong negative impact, Balance of Payment (-690%) had negative consequences, which is counter-intuitive.

Thirdly, we performed the quasi-experiment to see the counterfactual impact of Japanese FDI with the EU. Over many combinations of determinants, corporate tax and labor productivity showed good explanatory powers- with this simple model, we run DID analysis to show the Korean-EU FTA impact on Korean FDI. After DID analysis, we measured 317% (Panel regression with dummies) pure result of FTA impact on FDI. From Japan-EU FTA, the EU might be able to welcome 732% additional FDI from Japan. We also extrapolate similarities and differences between Korean and Japanese inflow. The EU policymakers can focus on marketing Labor productivity and lower corporate tax and VAT if they are willing to take disadvantages from it. FTA promotes commerce and knowledge exchange between economic blocs: It promotes FDI inflow as well the EU had more than a 300% beneficial investment impact after signing FTA with Korea. By signing FTA with Japan, the EU might welcome over 700% additional Japanese FDI inflow.

6. Appendix

a. Detailed definitions of variables

Variable	Definition
FDI	Share of Foreign Direct Investment to GDP
GDP(RGDP)	Real Gross Domestic Product (nominal GDP deflated by the GDP deflator)
GDP_EURO_PPP	GDP Per capita in Euro
SCHO_SEC(HUMCAP)	Level of Human Capital (proxied by the secondary school enrolment rate)
GDP_GROWTH(G.R.)	Market size (measured by annual % change in real GDP)
INTEREST(RLIR)	Real Interest rate (measured by the difference between the nominal lending interest rate and the rate of inflation
GFDI	Gross Fixed Domestic Investment (proxied by the share of the gross domestic capital formation to GDP less net FDI inflows)
OPENNESS(OPEN)	The openness of the economy (measured by the ratio of trade exports + imports to GDP)
QUAL_INF(INFRAC)	Infrastructure (proxied by the electric power transmission and distribution losses as a % of the total output)
INF(INFL)	Inflation rate measured by the annual percentage change in the consumer price index
TDS	Total debt service to GDP ratio majorly measured by the share of entire external debt service to GDP
CPI	Corruption Perception Index
ROI	Return on investment using proxies of long-term U.S. interest rates
GOVSIZE	Government consumption majorly measured by the share of the total government consumption to GDP
PGDP	Per Capita Gross Domestic Product ($)
HDI	Human Development Index Value
Education	Education Index (a sub-dimension of HDI)
Health	Health Index (a sub-dimension of HDI)
ECONFR	The Value of the Economic Freedom Index
EASE_BIZ	Easiness of Business
Time_Paper	Time of paperwork needed to start a new business
VAT	representative VAT rate
LPI	Labor Productivity index
Labor_COST	Level of Labor cost
Income_GINI	Gini index in terms of income
HighTEC_Export	high tech product export index
ACC_BAL	Balance of Payment, corresponding country and year
KOREA	Dummy for pooled OLS, if Korea, then 1 otherwise 0

b. Eurostat glossary

http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Foreign_direct_investment_(FDI)

Glossary: Foreign Direct Investment (FDI) is an international investment within the balance of payment accounts. A resident entity in one economy essentially seeks to obtain a lasting interest in an enterprise resident in another economy. An abiding appeal implies a long-term relationship between the direct investors and the enterprise and an investor's significant influence on the enterprises' management.

A direct investment company is one where a direct investor owns more than 10 % of the ordinary shares or an incorporated enterprise, voting rights, and an unincorporated company equivalent.

FDI flows and stock: through direct investment flows, an investor builds up an FDI position that impacts an economy's international investment position. This FDI position or FDI stock is different from the accumulated flows because of some revaluations, such as changes in prices or exchange rates, and other adjustments like rescheduling or cancellation of loans or debt-equity swaps.

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CAPÍTULO 3: European mobile phone industry: Demand estimation using discrete random coefficients models

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Abstract

This paper combines the literature from marketing and industrial economics about the mobile industry to build up the basics for estimating heterogeneous demand models. We also had a look at the general statistics for better understanding the market and proposing logit and Random Coefficient Logit (RCL) models to estimate the demand equations. Based on the observation on the market and the aggregate format of the market intelligence data, we follow the methodology of (Berry, et al., 1995) and (Nevo, 2000) since we consider their approaches an attractive fit for estimating discrete purchases demand from aggregate data. Our approach's significant contribution is to provide a practical method for estimating price elasticities for demand systems involving many similar datasets using market intelligence data. The applications to other related electronics industry would be quite simple, considering the similarities in characteristics, perishable nature of selling prices, heterogeneous demand, and demographic differences in tastes.

Keywords

Random Coefficient Logit, BLP, economic analysis, Mobile Phone Industry, Heterogeneous demand, Amazon-cloud, forecasting, demographic differences

JEL Codes

C35, C36, C53, D12, L11, L21, L63, L96

1. Introduction

Estimating demand systems is crucial for answering many managerial and policy-related questions, as shown in industrial organization (IO) and marketing literature. Discrete Choice Models(DCM) have a long tradition in empirical research. They were developed initially by (McFadden, 1974) starting with a rigorous theoretical model in which agents maximize utility (or profit) functions to analyze consumer choices with micro-level data. Here there are no "taste" impacts on consumers; this keeps the "representative agent" concept (henceforth "structural approach"). The observable characteristics are the same across all consumers. Though this hypothesis is sometimes reasonable and sometimes counterintuitive depending on the context, it makes the model simpler. In the classical work of (Berry, et al., 1995) (BLP hereafter), they relaxed this hypothesis and introduce different tastes among consumers, i.e., unobserved heterogeneity in consumers' evaluations of product characteristics. They propose an RCL demand model estimated with aggregate data on sales, prices, and product characteristics. The BLP method is a way to predict demand curves, an idea that lends itself to testing theories of IO. The beauty of BLP is that it can combine a variety of new econometric methods with many optimization techniques, and it is flexibly adaptable to other contexts. We use this structural approach to ensure a self-consistent setup and test much more elegant hypotheses about economic behavior at the cost of complexity and absence of robustness to specification errors.

Since random coefficients account for unobserved heterogeneity in consumer evaluations of product characteristics, they create flexible substitution patterns between products. Since (Nevo, 2000)(Nevo hereafter), the aggregate RCL model has become increasingly popular in IO, marketing, international trade, management, environmental economics, and many other areas of economics. BLP's RCL model generates a nonlinear aggregate market share system. Then, BLP shows how to invert the system to solve the product-specific unobservables and estimate the model using Generalized Methods of Moments (henceforth GMM) estimators. In the literature, we find several papers documenting numerical difficulties with BLP's approach and often based on Monte Carlo studies, attempting to formulate solutions. This potential computational burden has brought about alternative estimation methods and computationally light procedures. (Dubé, et al., 2012) assess BLP's contraction mapping performance, a Nested Fixed Point (NFP) algorithm to invert the market share system. They propose an approach called Mathematical Programming with Equilibrium Constraints (MPEC). This algorithm virtually eliminates the inner loop contraction mapping, which can computationally expensive and instead solves a minimization problem of the GMM objective function subject to the market share system as constraints.

Many papers in marketing and IO deal with the theoretical basis of a company's product and pricing strategy. (Anderson, et al., 1988) use the discrete choice model to describe various product firms in the context of spatial price discrimination. Moreover, they show that many strong properties of the standard homogeneous goods case are no longer valid. The social optimum as a market equilibrium is no longer sustainable unless products are either identical or very different. (Anderson, et al., 1992) presents the multinomial logit model to describe the demand of a heterogeneous population for a set of differentiated goods. (Gallego & Wang, 2014) study companies selling multiple differentiated substitutable products and customers whose purchase behavior follows a nested logit structure. Customers make purchasing decisions sequentially: they first select a nest of products and subsequently purchase a product within the selected class. It shows that each nest has an adjusted nest-level markup that is nest-invariant, which further reduces this problem to a single variable optimization of a continuous function over a bounded interval and provides conditions for this function unimodal. We also use those results to simplify the oligopolistic price competition and characterize the Nash Equilibrium (NE). (Armstrong & Vickers, 2015) provides relatively simple necessary and sufficient conditions for a multiproduct demand system generated using a discrete choice model with unit demands.

We are entering into the world of the internet of things (IoT); for the time being, smartphones are at the center of this world due to connectedness, and infrastructures support smartphones to connect with other machines. Therefore, the mobile phone sector's demand systems' estimation is relevant since it will continue to constitute or evolve into one of the most critical parts in the future. That is one reason why the mobile phone sector is a field with high innovation and customer churn, where the struggle for market share has been positively fierce. While many academic types of research deal with the mobile industry and mobile operators' and manufacturers' marketing strategies from the business perspective, many studies still focus on network operators due to their strong influence on the value chain. (Suryanegara & Miyazaki, 2010) examines the Japanese mobile industry focusing on how mobile operators replied to market and technological changes, emphasizing how the brand image made created the most economical value and convergence on technological evolution. (Freire Kastner, 2012) explores, in the context of UK mobile telecommunication companies, theoretical explanation of pricing structure, the current pricing practices in actual business, and their connection to the obtained empirical evidence. He states that price is a crucial element for firms as it can influence demand and, consequently, profits. He emphasizes the importance of information in pricing behavior about customers and competitors. (Bhargava & Gangwar, 2013) compare pricing strategies of post-paid dominated mature mobile markets such as in the US with prepaid dominated growing markets such as India. They develop a model to explain India's pricing strategies and propose evolutionary steps to adapt their approach as the market matures. (Kim & Lee, 2010) study the South Korean mobile market and investigate the key drivers that establish and maintain customer loyalty to mobile telecommunications service providers. (Bidyarthi, et al., 2011) perform a case study of Nokia in India and show how pricing strategy can strengthen its market potential and cause room for new competitors' entries. (Prasad & Sahoo, 2011) perform value chain analysis in the mobile phone industry and find out that under the given scenario, developing a core competence shall provide an immense boost to the companies' performance from the costing as well as a marketing point of view. (Dedrick, et al., 2011) uses quantitative analysis of value captured by firms in the supply chain of mobile phones. They find even though telecom operators still have a significant portion of the gross profit in comparison to other handset manufacturers, when it comes to operating profit level, brand-name handset manufacturers capture similar financial value from each phone than any of its suppliers. Therefore, many handset manufacturers try to enhance brand recognition via R&D and marketing. (Kraemer, et al., 2011) show that Apple makes good examples of profits and reinvesting in these sectors, capturing a large share of value from brand awareness. While these products, including those produced in China or other developing countries, the main benefits are reinvested in its product design, software development, product management, and marketing. However, the main prerequisite of investment in both R&D and marketing is profit; therefore, many manufacturers strive to find room for more gains by reducing costs and increasing selling prices. Therefore, cost reduction via production optimization, streamlining processes, and logistics is an excellent subject in many electronic companies. However, companies have a great motivation to optimize their pricing strategies, which will allow them to reinvest and survive in the industry.

In this paper, we use readily available market intelligence data with information on consumer choice, and we show how they can help identify demand parameters in a widely used class of differentiated product demand models. Our paper's demand framework follows the setup and method (Berry, et al., 1995), using GMM estimators of the aggregate RCL model. We have market intelligence data containing aggregate choices, prices, types, countries, and brands' features. We use very common setups and structures of many random utility models in IO papers and adopt many aspects of the demand models of BLP and (Nevo, 2000). In these models, they describe the products as bundles of characteristics, and consumers choose the product that maximizes utility derived from product characteristics. We seek to uncover demand parameters to obtain a detailed analysis of past events to make realistic predictions.

Our primary purpose is to estimate demand systems for the mobile phone industry using market intelligence data from various sources. To answer any question in marketing and IO, we need to understand how consumers behave and make purchase decisions among many goods or services as a function of the market and individual characteristics. Estimating the underlying parameters will allow us to get many insights, as price elasticities. We like to show that it is possible, using aggregated data, to capture critical features of the corresponding distribution of consumers' willingness to pay; in other words, we want to estimate the proper demand system. Even though assessing and evaluating demand systems is a fascinating subject, it becomes even more interesting since it is necessary to obtain related parameters to get those demand systems. Moreover, this process is often used in various fields to answer further questions to provide a more comprehensive picture.

We want to estimate elasticities of demand (d) and supply (s), assuming linear relationships (we will relax this condition later). The implication is that we want to estimate β, γ, the demand parameters or individual-specific taste coefficients; θ, λ , one observes the supply parameters, and also observes x product attributes (of brand j in market m), p is the price and ε_d and ε_s are demand and supply idiosyncratic shocks

$$d = \beta p + \gamma x + \epsilon_d$$
$$s = \theta p + \lambda x + \epsilon_s$$

The main issue of this setup is endogeneity. Variables affecting the supply shock (ϵ_s) or the demand shock (ϵ_s) will also affect the equilibrium price. Therefore, p is endogenous in both equations. We need at least an instrumental variable, changing prices but independent of the demand curve, to estimate demand. Our basic framework of modeling and estimating follows the setup and method of BLP and Nevo. It uses a GMM estimator for the RCL model. In principle, BLP or RCL does not only solve endogeneity. Although the basic idea goes around an IV-logit, it allows for a more general model without assuming linear demand and supply. However, in a more complicated demand system, we need to be more careful with the instruments' choice and use. BLP demand function has its base in a Probit choice model (there is a continuation of agents receiving product specific shocks that determine their preferences). When integrating over agents, we arrive at a logistic demand system. This demand system typically bases on firms having linear cost functions and playing a differentiated Bertrand pricing game. For each guess of the model's parameters, we should compute the probability for each price-quantity combination as a function of observed covariates. Since we do not have exact solutions, we calculate the maximum likelihood at each outcome using GMM instead of 2SLS to estimate the parameters. The data contains aggregate choices, prices, types, countries, and features of the brands. Therefore, the BLP setting is an excellent choice since its design estimates demand in differentiated product markets using aggregate data.

Estimating the parameters of a demand system in the mobile phone industry will allow us to understand consumers' market and behavior better. This paper adjusts a dynamic demand model in conjunction with essential product characteristics to change consumers' decisions in the market for mobiles. It contributes to the existing marketing and empirical IO literature on dynamic, durable goods in three ways. First, we use demographic data for random interactions for heterogeneity to give "taste" impacts and individual abnormalities. We relax the heterogeneity hypothesis of structural models at the cost of making the solution more difficult. We show that the lack of microeconomic data can be dealt with by alternative approaches, and we employ demographics obtained and simulated from macroeconomic data. The BLP method captures more abundant forms of product differentiation and a more flexible distribution of consumer heterogeneity. Second, we use wildly available market intelligence data to estimate the mobile phone industry's complex demand structure. As we will see in section 2, from the viewpoints of importance, policy and market changes, profit, and pricing, estimating the mobile phone industry's demand systems is an essential and meaningful field. Since our data contains the price and non-price related characteristics of cell phones, we would be able to get information about substitution patterns between products and success factors in the current market. Finally, we use cost data from the mobile phone industry as instrumental variables to deal with price endogeneity and guarantee consistent estimation of the parameters. By instrumenting price using 2SLS (and GMM), we do not need to obtain the model's marginal costs. We discuss the importance of handset manufacturers and handset prices as a crucial factor of success and provide a useful tool for policy-makers.

Moreover, many market intelligence data are available these days since PoS data and big transaction data are available. Whereas traditional profit/non-profit agencies are publishing aggregate data, many are open source on the aggregate level. Therefore, we also think that it is an interesting academic question of whether we can recover consumer heterogeneity from combinations of many forms of aggregate data and micro-economic demographics.

The rest of the paper is as follows. In the next section, we present the history and current trends of the mobile industry. Section 3 displays the model used to simulate the industry structure. Section 4 reports the data used, including short summaries of the raw data set, joint with the theoretical framework, and Section 5 provides results, discussions, and implications. Section 6 reviews study findings and conclude the paper with theoretical and managerial implications, limitations, and future research directions.

2. Mobile Phone Industry

Network operators worldwide played the leading role in the mobile phone industry up to the mid-2000s, mainly due to entry barriers. They used to specify everything from the hardware to the applications and services included on the mobile handsets they sell (Anon., 2010). Consequently, mobile manufacturers played a minor role, and they need to support these requirements and personalize devices for individual operators effectively. Therefore, the primary studies about the mobile industry have focused on network operators and consumer behavior. After the advent of iPhone and Android phones in the 2010s, mobile operators and mobile manufacturers face a new competition phase. The fully maturing mobile industry is now facing recent changes and challenges. Due to economic policies favoring competition, mobile virtual network enablers (MVNE), and similar service quality, as the infrastructures get better in the developed world, mobile operators are losing oligopolistic power to get more customers.

Moreover, Apple and Android smartphones' arrival made manufacturers' role more crucial in terms of competition. Even if network operators still hold the leading position in this battle of the brand, mobile manufacturers' importance in this game increases and already influences operators' decisions using their real market power. Therefore, cooperation and competition between network operators and manufacturers are becoming critical factors in this industry.

Mergers and separations

The main reason is increasing competition due to separations (Cave, 2006), who discusses various, complete, or partial separation options of the ownership (Anon., 2019). 1) Legal separation (different legal entities under the same ownership); 2) business separation with varying arrangements of governance; 3) business separation with localized incentives; 4) virtual separation; and 5) separation through the creation of a wholesale accounting division. We can divide these separations can into two dimensions:

A. **Horizontal:** More competition in the mobile network business and less differentiation in service quality by network providers. In a recommendation to national telecom regulators (NRAs) issued by the European Commission, they called on public mobile telephone networks in 2003 to increase the market competitiveness for wholesale access. Consequently, in several countries, including Ireland and France, policy-makers made new regulations forcing operators to open networks to mobile virtual network operators (MVNOs).[2]
B. **Vertical:** As vertical separation increases due to high competition (price as well as non-price), operator service quality (non-price), as well as cost, is becoming less differentiable (Cave, 2006).

Market growth and competition

[2] See also *La lecture par l'Autorité de régulation des télécommunications de l'article L.1425-1* (2005). An MVNO is a wireless communications services provider that does not own the wireless network infrastructure over which the MVNO provides services to its customers.

Since the 2000s, the mobile phone market is growing fast, and the sales reached almost 2 billion euros per annum, only in the European Union (EU). Consequently, despite high entry barriers due to technology and capital-intensive requirements, more and more manufacturers join the market to gain market share. There were winners and losers in this industry from the beginning of the new millennium. However, after 2010, the competition is getting fierce. One of the significant reasons is well-equipped Chinese manufacturers with high technology and experiences from their big domestic market, targeting the entire world. Even if the growth seems to stabilize and the market appeared to be mature in 2015, expected demand from emerging economies and spillover effects (making smartphone facilitating related gadgets in the future) makes this industry still attractive.

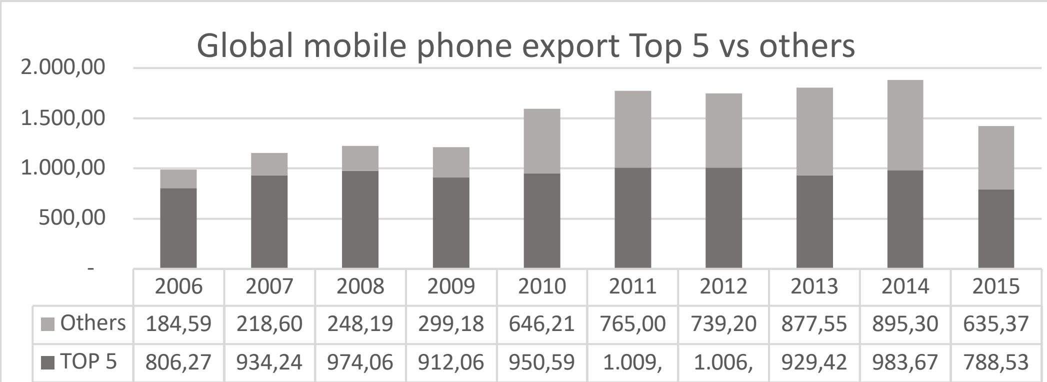
For many manufacturers, the mobile phone market is not a cash cow or profit center anymore because of this ever-growing fierce competition. However, it is difficult to abandon the mobile market due to 1) big market size, 2) high sunk costs for investment, and 3) spillover effect to other related electronics future areas in the IoT world. In a perfectly competitive market like commodities, the microeconomic theory suggests that manufacturers cannot find room for profit. Therefore, a mobile phone manufacturer's long-term strategy for survival should be differentiation. 1) investing in R&D to make making their product unique and 2) investing in marketing to improve the perceived value of their products and to build a differentiating brand image for consumers to avoid competition., namely increasing brand awareness, product exposure (PR).

Price and profit

The globally harsh competition, mainly from China, has made the mobile market a red ocean, cutting down average consumer prices. In the EU telecommunications service, prices fell yearly by an average of 11-13% between 2006 and 2010 (in comparison, fixed-line prices fell by only 5% per year from 1998 to 2010). For mobile manufacturers, figures for 2015 suggest that only two leading mobile manufacturers (Apple and Samsung, 92% and 15% respectively) profit from Mobile business, indicating other players account for -7% loss. Table 1 shows the export proportion of the prominent five mobile manufacturers vis-à-vis the rest. It shows that the market share of 5 manufacturers accounted for more than 80% in 2006, but it became less than 50% after 2013.

Price discrimination is one of the most common forms of marketing practices and a direct way of regaining profit. In the electronics industry, most manufacturers are still using cost-plus or competition-based pricing mainly due to the convention of being under high price competition even though many leading companies are now learning about the importance of value-based pricing and adopting it company (Hinterhuber, et al., 2012). There could be many ways of completing other manufacturers, and they cost reduction in production, economies of scale, efficiency improvement in the organization by reducing fixed costs and logistics. However, all of them only can be achieved via significant efforts, investments, and continuous improvements. We know that the players can meet all those goals through long-term efforts. The easiest way of increasing the short-mid-term profit of products in production or a near-production phase would be profit optimization. However, with the ever-growing competition, consumers may switch to alternatives if they notice this seller surplus. Thus, consumers will choose other options with higher customer values, putting increased pressure on the manufacturers and operators to invest more in R & D and marketing for innovation, better productivity, and better market awareness.

Table 1 Global mobile phone market (big 5 vs others)



3. The Model

Since our main objective is to estimate a complete demand model, we start with the well-known classical aggregate logit model; then, we turn to the aggregate RCL model. We assume a set of markets, m = 1, …, M, where the same set of products, j = 1, …, J, is available in each market (or/and time).[3] We denote not-purchasing by j = 0 and individuals by i = 1, …, N (N is large).

We express the utility of consumer i from purchasing product j in market m as:

$$\boldsymbol{u_{ijm}} = \boldsymbol{x_{jm}\beta_{ijm}} + \boldsymbol{\alpha_i(y_i - p_{jm})} + \boldsymbol{\xi_{jm}} + \boldsymbol{\varepsilon_{ijm}} \qquad \textit{(1)}$$

Where x_{jm} are observed product attributes of brand j in market m; p_{jm} is the price of purchasing product j in market m; ξ_{jm} are unobserved product characteristic (demand shifters different by brands and markets); y_i is the income of the consumer i and ε_{ijm}, an idiosyncratic shock is assumed to be Type I extreme value distribution, independently and identically distributed across products, consumers, and markets. The other terms of (1) are parameters, which can be defined: α_i is i consumer's marginal utility of income and β_{ijm} are demand parameters or individual-specific taste coefficients (varying by individuals, product, and markets)., Finally, for identification purposes, we assume $U_{i0m} = \varepsilon_{i0m}$.

As mentioned, x_{jm} is a vector of observed product attributes, including a constant and β_i represents the taste of consumer i, and it is assumed to follow a distribution F (·; θ) where θ is a K-vector of parameters to be estimated. As expressed in (1), we can make consumer preferences vary with individual characteristics as in (Nevo, 2000), introducing the concepts of observed "demographics"- D_j - and "unobserved" tastes, v_j. Collecting all terms, we can express the model in matrix notation as:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \boldsymbol{\Pi}\, \boldsymbol{D_i} + \boldsymbol{\Sigma v_i} \qquad \textit{(2)}$$

$$with\ v_i \sim {P_v}^*(v)\ ,\ D_i \sim {\hat{P}_v}^*(D)$$

Where ${P_v}^*(v)$ a parametric distribution, ${\hat{P}_v}^*(D)$ is a nonparametric distribution known from other data sources.

[3] We omit time subscripts for maintaining notation simple.

If we define an outside good and normalize its utility to zero, we can split vector θ into the linear parameters $\theta_1 = (\alpha, \beta)$, nonlinear parameters $\theta_2 = (\Pi, \Sigma)$, and we can combine (1) and (2) to obtain the following expression:

$$u_{ijm} = \alpha_i y_i + \delta_{im}(x_{jm}, p_{jm}, \xi_{jm}; \theta_1) + \mu_{ijm}(x_{jm}, p_{jm}, v_i; \theta_2) + \varepsilon_{ijm} \qquad (3)$$

$$\delta_{im} = x_{jm}\beta - \alpha p_{jm} + \xi_{jm}, \; \mu_{ijm} = [-p_{jm}, x_{jm}](\Pi\, D_i + \Sigma v_i),$$

With δ_{im} being an average utility (common to all customers), $\mu_{ijm} + \varepsilon_{ijm}$ a mean-zero heteroscedastic deviation from average utility capturing the effects of the random coefficients and the first term $\alpha_i y_i$ vanishes. Consumers choose the option of giving the highest utility. BLP illustrates that, by specifying ε_{ijt} as a Type I extreme value distribution, parameters in (3) can be estimated. From the distributional assumption of ε_{ijt}, the probability of consumer i purchasing product j in market m is given by:

$$\frac{exp\,(x_{jm}\beta_i + \xi_{jm})}{1 + \sum_{j'=1}^{J} exp\,(x_{j'm}\beta_i + \xi_{j'm})} \qquad (4)$$

Where $x_j \equiv (x'_{1m}, \ldots, x'_{Jm})$ and $\xi_m \equiv (\xi'_{1m}, \ldots, \xi'_{Jm})$.

The model aggregate market share function integrates over the consumer-specific choice probabilities, where we let $dF(\beta_i; \theta)$ denote the population distribution of consumer heterogeneity.

The prediction of the market share of product j in market m is then:

$$s_j(x_m, \xi_{im}; \beta_i) = \int \frac{exp(x_{jm}\beta_i + \xi_{jm})}{1 + \sum_{j'=1}^{J} exp(x_{j'm}\beta_i + \xi_{j'm})} dF(\beta_i; \theta) \qquad (5)$$

Often, the evaluation of this integral requires simulation. If we generate β_i for i = 1, …, N,

$$s_j(x_m, \xi_{im}; \beta_i, N_s) = \frac{1}{N_s} \sum_{i=1}^{N_s} \frac{exp(x_{jm}\beta_i + \xi_{jm})}{1 + \sum_{j'=1}^{J} exp(x_{j'm}\beta_i + \xi_{j'm})} \qquad (6)$$

Moreover, using the market shares are defined by equation (6), we can get the price elasticities of corresponding markets from the aggregate logit model:

$$\eta_{ikm} = \frac{\partial s_{jm}}{\partial P_{km}} \frac{P_{km}}{s_{jm}} = \begin{cases} -\alpha p_{jm}(1 - s_{jm}) & if\; j = k \\ \alpha p_{km} s_{km} & otherwise \end{cases} \qquad (7)$$

So far, we have reviewed the concept of the underlying discrete choice random utility model for each good with an extreme distribution of error, leading to a logit probability of purchase. We now turn to elasticities in (7). This equation implies some potential issues when the distribution of ε_{ijt} is assumed to be Type I extreme value. First, since the market shares are small in most cases, the factor $\alpha p_{jm}(1 - s_{jm})$ is nearly constant; this provides own-price elasticities proportional to price. This fact indicates, the lower the price, the lower the elasticity's absolute value, meaning the lower-priced brands would have a higher markup when priced based on a basic pricing model. This conclusion would be only valid if cheaper brands' marginal costs are than that of a more expensive product lower (not just in absolute value, but as a percentage of price). The second problem, which we find mainly stressed in the literature, concerns cross-price elasticities. If many products with similar or distinctive characteristics have equal market shares, then the substitution from one towards another will always be the same, regardless of the similarities in characteristics. In other words, the logit model restricts consumers to substitute towards other brands in proportion to market shares, regardless of traits. In general, this is called Independence of Irrelevant Alternatives (IIA) property, i.e., how this structure implies weird substitution patterns for goods that might be close to each other due to the iid assumption shocks. Since the problems with cross-price elasticities come from the iid structure of the random shock, allowing ε_{ijm} somewhat correlated among products would be an adequate approach.

Assuming Generalized Extreme Value (GEV hereafter) distributions is a suitable alternative in this setup. The GEV models allow various substitution patterns to introduce correlations over other options. One of the most well-known and intuitive GEV models is the nested logit model. The alternatives are divided into subsets (nets), relaxing the IIA property since it adds individual-specific slopes to the utilities, resulting in better substitution patterns at the aggregate level. There are many papers on the nested logit and GEV models that deal with these two issues. However, in our case and similar cases, we do not have a priori information about the market to perform the division of products into groups. Moreover, we have to assume the shocks' distribution within a group when performing the demand estimation.

This fact is one crucial reason why we propose to use RCL models. Now, we have to turn to the aggregate version of the RCL model. In this model, now we also try to estimate an unrestricted variance-covariance matrix of the shock, ε_{ijm}.and this relaxes all the abovementioned issues. However, this does not come without cost. First, we need to deal with "the curse of dimensionality." This problem occurs because the number of parameters that we need to estimate will explode - a problem that aggravates by the number of products and markets -. If there are N products in M markets, there are N*M demand curves, and since the demand curve of each product depends on the prices of the others, there are at least N^2*M parameters in the model.[4] However, if we maintain Type I extreme value distribution of ε_{ijm}.- and introduce demographics - there will be some correlation between products with similar characteristics. This method is how (Nevo, 2000) deals with errors and also helps with the curse of dimensionality. In this setup, the consumers with similar demographics will have similar rankings of products and, therefore, identical substitution patterns; and we capture the correlation between choices through the term μ_{ijt} . The correlation is a function of both product and consumer characteristics. Therefore, in this setup, now we have to estimate a smaller amount corresponding to an unrestricted variance-covariance matrix rather than evaluating a large number of parameters

With reduced settings from (Nevo, 2000)'s setup, which facilitates reducing errors and helps with the curse of dimensionality significantly.

Now following (Nevo, 2000), the price elasticity of brand j in market m is:

$$\eta_{ikm} = \frac{\partial s_{jm}}{\partial P_{km}} \frac{P_{km}}{s_{jm}} = \begin{cases} -\frac{p_{jm}}{s_{jm}} \int \alpha_i s_{ijm} \left(1 - s_{jt}\right) d\hat{P}_D^*(D) d\hat{P}_v^*(v) & if\ j = k \\ \frac{p_{kt}}{s_{jm}} \int \alpha_i s_{ijm}\, s_{jkm} d\hat{P}_D^*(D) d\hat{P}_v^*(v) & otherwise \end{cases} \quad \textit{(8)}$$

$$s_{ijm} = \frac{\exp\left(\delta_{jm} + \mu_{ijm}\right)}{1 + \sum_{k=1}^{K} \exp\left(\delta_{km} + \mu_{ikm}\right)} \quad \textit{(9)}$$

where s_{ijm} is the probability of individual i purchasing product j.

[4] It might be better to feel the difficulty in the reality of our dataset. Even without considering characteristics and demographics, we will already have to estimate at least N (number of products)^2*M(number of markets)*36 months. For our final clean dataset, this means 4,148,928 parameters.

4. Data and estimation

4.1. <u>The data</u>

We intend to estimate the model with monthly information on European mobile phone sales, prices, and product characteristics. After mandatory fields for models are defined, the database was constructed, cleansed, and aggregated into one market intelligence data. The raw data comes from Eurostat, Statista, European G2k, ITC, and other third-party websites freely available on the web. Then, we combine this data into one relational database. It had 40 fields containing various information brand, model, price, and channel types. It initially gives us practical difficulties for data management. It is also computationally challenging because the numbers of product-market combinations exploded the dimensionality (more than two million parameters). To investigate further with combined data, we first define the limits of our study. In particular, in our case, we are mostly interested in analyzing how manufacturers' product line-up, their products' characteristics (specs), and the promotions and subsidies of brands affect manufacturers' substitution patterns and pricing decisions. After running a panel survey and a series of reduced-form regressions, we have selected the following choice set. Our Tables 2, 3, 4, and 5 illustrate the evolution of our choice set in the aspects of countries, brands, price, and demographics, respectively. Table 11 in the Appendix shows the detailed specifications of selected variables during selected periods for some prominent chosen brands.

The choice set

First, we had to define the set where consumers make choices. We deal with these computational challenges using new estimation algorithms and cloud computing, which is another way of dealing with big data, but this is not within our paper's scope. We are more interested in defining a proper choice set that would represent our setup's effectiveness. To define a choice set, we had to classify main models of interest into a list of distinct models and associated characteristics and quantities sold. We determine the final plan by the market shares, expert panels, and lists from third party websites. Out of full data, for the reason of practicality and simplicity, we decide to use monthly data, therefore aggregated monthly to the product level across ten national markets from January 2014-June 2016 per channel and brand (98 products), as described below. Our final sample has 36 months, ten countries, and 98 products, i.e., 29400 observations. We show some details and statistics per category below both in the main text and the Appendix. The primary data contains market shares and prices in each market, dummies, and model characteristics. Also, information on the distribution of demographics, some instruments that we consider correlated with the market share but uncorrelated with the price such as marketing mix variables, supply-side information (production cost), and some product characteristics (i.e., operating system). As for the product characteristics, which is one of the essential parts of any data set required to implement this kind of model, we include physical product characteristics and market segmentation information. As (Nevo, 2000) indicates, we use product characteristics to explain the average utility level δ_{im}, and cover the substitution patterns through μ_{ijm} in equation (3).

We mainly collect this information from manufacturers' official product descriptions or our prior experiences assisted by expert panels and external sources. Namely, during the data cleansing phase, we gathered and corrected these data directly from online catalogs and product descriptions from Amazon or other websites,[5] which collects this information mainly from manufacturers' websites. In the rare case of missing or conflicting information, we would directly refer to the manufacturers' homepages. We sometimes referred to the most similar models' specifications or excluded them entirely from the analysis.

As for demographics, we used the same settings as in (Nevo, 2000), who used for its examples, namely, income, income squared, age, and children's presence. Here, since our estimation will rely on assumed distributional assumptions, data is generated with distributional assumptions from macroeconomic data. As for income, we

[5] Some sites are www.idealo.de, www.gsmarena.com, www.kimovil.com, or www.bardtech.

use the lognormal assumption. Statistics differ annually. We denote the estimated mean and the standard deviation by the Eurostat "Distribution of income by quantiles." This data allows us to use the available information on income distribution to increase our estimation procedure's efficiency.

Now, we summarize the variables included either as regressors or instruments in our analysis. Time variables are year and month. The model/channel is an operator, the month when the model is introduced, the family model, global region, brand, and country. The price is considered as segments (in euros) and tier by euro. Grouping is considered a channel, model, product ID, channel group code, channel group, and product group. We use monetary and physical sales (euros and units). Since the data is extensive, monthly data for 36 months are selected (January 2014–June 2016), and they are aggregated to the country-level (separated per channel, model, and brand) for ten selected countries. Table 2 summarizes sales (in thousand €) in these countries. There was about 22.2 billion € worth of mobile phones sold in 2011, while in 2016, the amount increases 48 percent to 32.8 billion. We limit the estimation for this period due to the complexity of showing elasticities. Therefore our primary purpose here is to give an illustrative application of applying our methods. However, once we estimate, the model can be dynamically updated by adding one more dataset per month per country, which might be meaningful, especially for mobile marketers interested in the demand curve changes.

Table 2. Sales in selected countries (in thousand €)

Country	2011	2012	2013	2014	2015	2016
Austria	791,508	794,001	892,178	860,162	994,822	1,078,943
Belgium	567,991	717,976	758,599	883,180	1,013,176	1,091,769
Czech Republic	415,665	415,059	451,472	500,241	622,231	657,507
France	4,708,800	4,660,583	4,667,221	5,258,093	4,937,294	5,066,069
Germany	6,033,516	7,358,477	8,340,855	9,007,173	9,978,009	9,666,165
Italy	3,453,280	4,230,630	5,124,371	4,993,160	5,888,468	6,197,628
Netherlands	1,478,885	1,628,413	1,660,531	1,826,805	2,243,070	2,435,477
Poland	1,260,335	1,380,539	1,389,297	1,404,264	1,834,921	2,130,351
Portugal	364,896	444,490	558,634	748,981	818,624	836,546
Spain	3,145,310	3,090,737	3,266,396	3,678,116	3,931,650	3,658,015
Grand Total	**22,220,188**	**24,720,905**	**27,109,553**	**29,160,175**	**32,262,265**	**32,818,470**

Table 3 provides some insights into the data. In terms of country-brand market share, the data shows heterogeneity and homogeneity at the same time. On the one hand, we observe global manufacturers like Apple and Samsung dominating the market. However, we can also follow country-specific market winners in some countries, such as Wiko, Alcatel, or Huawei. Outside goods show, in general, a market share close to 10 percent, except for the Czech Republic and Italy.

Table 3. Market share average per brand during Jan 2014-Jun 2016 (%)

	Austria	Belgium	Czech	France	Germany	Italy	Netherlands	Poland	Portugal	Spain
Alcatel	0.70	0.45	0.79	0.76	0.35	2.95	0.69	0.39	2.60	1.59
Apple	37.56	40.85	23.12	35.96	42.83	23.66	32.88	48.11	21.08	28.55
Blackberry	0.46	0.23	0.32	0.16	0.53	0.05	0.06	0.12	0.03	0.03
Htc	0.75	0.40	0.59	0.64	1.09	0.54	0.18	0.72	0.01	0.29
Huawei	10.13	10.12	12.52	3.81	5.04	8.69	14.95	4.60	13.68	15.87
Lg	2.59	1.10	2.09	1.13	1.35	4.39	2.30	2.17	2.59	4.24
Microsoft	1.24	1.35	2.18	1.16	1.21	1.46	1.22	1.35	1.30	0.19

Motorola	0.27	1.02	0.11	0.66	0.43	0.18	0.29	0.97	0.14	0.96
Nokia	0.54	0.87	1.45	0.21	0.17	1.76	0.40	0.21	1.05	0.06
Samsung	38.23	37.11	33.65	33.81	39.28	37.33	38.60	37.23	41.46	33.53
Sony	4.22	1.70	3.15	2.65	3.72	3.44	0.57	2.31	0.92	2.59
Wiko	0.13	1.56	0.00	6.77	0.81	0.00	2.08	0.33	4.91	1.31
Outside good	3.17	3.24	20.05	12.27	3.19	15.55	5.78	1.48	10.23	10.79
Total	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

Since the data is aggregated based on the same price sold in transactions, we have to compute the average and standard deviation for grouped data to analyze divergence in prices. First, we find the sales data of each channel, model per each time, and period. Then, we multiply the sales figure by the corresponding record frequencies, and we divide it by the quantity sold. To find the value of variances in price, and since we assume that those are only sample data, we use the following basic formulas:

$$s^2 = \frac{\sum m^2 f - \frac{(\sum mf)^2}{n}}{n-1} \qquad \textbf{\textit{(10)}}$$

Since the data is aggregated by nature, under some assumptions (below), standard deviations calculated using the formula, as mentioned earlier, will represent brand, model, and country-specific pricing strategies and price deviations at the end-consumers' level. Tables 16-19 in the Appendix provide some interesting summary statistics to illustrate raw data by brand, country, and price groups.

Assumption 1. A channel does not frequently change their prices within a month. Since we have monthly level aggregation data, "Frequently" changing prices without tendency (in consumables usually downwards) at the POS can make the standard deviation unreliable since data will only represent average prices. This status can happen, especially in Brick-and-Mortar stores where promotions exist, but these actives are infrequent (twice a year) in the Mobile phone industry.

Assumption 2. Even if Assumption 1 does not hold, there are downwards tendencies of prices. Brick-and-Mortar stores' up-and-down strategy can be captured by aggregation over months or a year and becomes negligible since a downward price tendency exists.

We define the following price variables — the price deviation index (Diff). The standard deviation of individual-level price data (by month, brand, model, channel, and country) is analyzed and aggregated again to the higher levels. There are two independent variables to represent price deviations that customers (or dealers) can capture in the long-run. i) Intra-country pricing variances. They are calculated based on a mobile phone model price variation over ten countries. Standard deviations are calculated on the model level and aggregated back to brand level or brand-price tier level (we denote this variable Diff_C). ii) Time-series variation. Time-series pricing variances are calculated based on a mobile phone model price variation over 12 months. Standard deviations are calculated on the model level and aggregated back to brand level or brand-price tier level (we denote this variable Diff_T). Monthly aggregated final price (p_{jm}) is the monthly average real price that consumers pay to the retailers. We define it as sales revenue divided by the number of units sold and deflated by the consumer price index.

Physical product characteristics (specifications)

Here we discuss the definitions of physical product characteristics and their data structures throughout the paper. The product characteristics in the vector (x_{jm}) we have selected from the data include Display Size, 1st Camera Resolution, 2nd Camera Resolution, Subsidy, Storage in GB, RAM in GB, HIG Resolution, CPU, CPU-CORES, Operating System, Display Techno (LCD, OLED, and others), max Generation, Keyboard, WiFi, GPS, Memory Card Slot, Bluetooth, Multi-Touch and NFC. Display Size is the diagonal measure of the phone's display area in inches; 1st / 2nd Camera Resolution is the number of megapixels on the mobile phone's camera (2nd: front/ 1st: back); subsidy is the money that manufactures and telecom companies for customers with contracts and marketing expenses (in Euro); storage IN GB is the storage capacity of the smartphone in gigabytes (GB); RAM IN GB is the total RAM capacity of the smartphone in GB; resolution HIG is the number of pixels in the screen, CPU is the speed in megahertz (MHz) of the central processing unit; CPU-CORES is the number of processors in the CPU; Operating System and Display Techno (LCD, OLED, etc.), are categorical dummy variables (Android, I-OS, SImbian, etc.) .....; max Generation is the max number of generation that the phone is compatible with (if is fourth-generation =4, if is third-generation=3, etc.), Keyboard, WiFi, GPS, Memory Card Slot, Bluetooth, Multi Touch, NFC are binary characteristics equal one when the phone has the technology and zero otherwise. Table 11 in the Appendix provides some examples by brand and model.

Segmentation information

Regardless of the actual selling price to the end-customer, manufacturers' intention on market positioning (often observed by Recommended Retail Price) level or consumers' perception about the product is one of its non-physical characteristics. We name it "Pricing Tier," it is used for detailed analysis and defined for the review. It consists of four tiers Basic: 0-199 €, Step-up: 199-349 €, High: 349-499 € and Premium: 499 and more €. We also use this segmentation information as an instrument in our estimation. Table 4 shows sales in EU selected countries per pricing tier (thousand €). In general, we can observe that Premium Tier's sales share increase during the period. This result can reflect many aspects of changes in the market and different patterns in customer's tastes since the market is saturated, and this category captures many early adopters without caring about owning more than one mobile phone.

Table 4. Sales in EU selected countries per pricing tier (thousand €)

Price Tier	Perceived value, €	2011	2012	2013	2014	2015	2016
Basic	**~49**	831,572	668,598	515,609	475,300	413,280	353,003
Basic	**49.xx~99**	2,466,517	2,022,796	1,709,771	1,710,751	1,711,648	1,313,021
Basic	**99.xx~149**	2,297,195	2,043,401	1,944,939	2,830,435	2,777,909	1,681,700
Basic	**149.xx~199**	2,023,004	2,127,943	2,503,964	2,613,989	3,052,613	3,694,499
Step-up	**199.xx~249**	1,708,019	1,843,908	1,930,798	1,746,353	1,794,736	1,940,465
Step-up	**249.xx~299**	1,383,555	1,302,008	1,551,755	1,497,427	1,705,285	1,762,605
Step-up	**299.xx~349**	965,906	908,810	1,375,948	1,831,513	1,153,360	1,739,553
High	**349.xx~399**	1,023,006	1,208,667	1,880,561	1,612,191	1,404,099	1,043,366
High	**399.xx~449**	1,296,489	1,138,897	1,378,845	1,123,721	1,516,964	881,411
High	**449.xx~499**	1,154,249	1,450,739	1,558,771	1,619,996	1,269,283	1,449,871
Premium	**499.xx~599**	2,989,614	4,104,295	3,559,221	3,166,976	2,044,846	2,696,831
Premium	**599.xx~699**	3,133,119	4,307,850	4,845,260	4,933,589	4,082,738	3,653,292
Premium	**699.xx~**	947,943	1,592,993	2,354,111	3,997,934	9,335,503	10,608,853
Total		**22,220,188**	**24,720,905**	**27,109,553**	**29,160,175**	**32,262,265**	**32,818,470**

Moreover, customer surveys suggest that consumers tend to upgrade their phones when the previous one gets old or breaks. Therefore, many high tier consumers might have migrated to Premium Tier.[6] Table 4 also shows

[6] Further discussion would be out of the scope of our paper. However, actually many other interesting facts are found based on the analysis of the raw data. Summary statistics are shown in the Appendix, Tables 16-19. We can observe, for example, that the number of models found in basic tier increase with time, while the actual sales portion of the same tier decrease. Then, there are high competition even though the demand is decreasing. This is due to low entry barriers for manufactures and saturation of European mobile market, making consumers prefer phones with better features. The number of models in Premium tier also increase with time, and consequently current sales portion of the same tier skyrocket. This explain why high-tier and premium markets are the focus of well-known firms (the cash-cow).

product by brackets and pricing group. Again, these figures represent only the expected perceived value of the purchase.

Demographics

We used the same settings as (Nevo, 2000). We downloaded all these data have from Eurostat (http://ec.europa.eu/eurostat/data/database). We assumed the income distribution to be lognormal, and we estimate its parameters and the demographics drawn from Eurostat, as briefly mentioned in Section 2 and detailed below. Ages and child data come on actual sample household data based on a questionnaire. To avoid disproportionate sampling among ages, we treated them to have a zero-mean value, then reshaped them to fit Eurostat population statistics. Therefore, we use the log of income (Income), the log of income squared (Income Sq), to allow for nonlinear profiles affecting demand, age, and a dummy variable equal to one of the individuals is aged less than nineteen (Child). The proxies for unobserved demographics, v_i, are drawn from a standard normal distribution. For each market, we draw 20 individuals. We assume that the v_i are random draws from a distribution obtained with zero mean value and an identity covariance matrix independent of the level of consumer's income (y_i). The interaction distribution is assumed to be lognormal, and we estimate its parameters and the demographics drawn from Eurostat. In detail, a log of income variable (Income) and the log of income squared variable (Income Sq) base on the "Income per sex, age" per country and year. We sample individuals populated for 300 (market size) * 20(individuals per market) to mimic microeconomic decisions varying by income. With the same principle and based on Eurostat's same data source, the age variable is populated per sex, age individuals are sampled for 300 (market size) * 20(individuals per market). We extract the child variable from the demographics that are from age variables. It is a dummy variable made by the criteria if the age is under or the same as 18, 0, otherwise 1.

For explanatory variables, we have tested over 200 pre-simulations, with many demographic combinations. In Table 5, we summarize some selected interactions with combinations that show exciting results. Several interactions between observed demographic attributes and some product characteristics stand out, including age, a child with display size, income squared with 1st Camera and CPU, Storage with age. While Income is assumed to interact with almost all product characteristic variables, Price interacts with all demographic variables. Let us discuss other combination alternatives in Section 5.

Table 5. BLP demand estimation – combinations and demographic interactions

	income	income squared	age	child
Price	1	1	1	1
Display Size	1		1	1
1st Camera Resolution	1	1	1	
Subsidy	1			
Storage IN GB	1		1	
CPU	1	1		

4.2 Estimation

We are going to estimate the parameters by GMM. We assume that the supply and demand unobservables are mean independent of both observed product characteristics and cost shifters. On top of the discrete choice model of demand, we want to estimate a structural model of manufacturer and model pricing in this channel. Our work's context is vertical channels competing for mobile manufacturers who sell through many conventional distributors, online and offline retailers. As we will see below, we model consumer heterogeneity with a finite number of discrete segments. This setup lets us better control the potential endogeneity due to the aggregated data's unmeasured product characteristics. We use demographics for instruments as well. We include cost data in the distribution channel model that captures essential features of manufacturers' aggressive price-setting behavior using available cost information and profit published by manufacturers.

4.2.1 The estimation setup and assumptions

As briefly mentioned, unobservables are mean independent of both observed product characteristics ξ_j an$\mathrm{w_j}$supply shifters, i.e.$E[\xi_j|(x_1, \mathrm{w}_1), (x_2, \mathrm{w}_2), \ldots, (x_J, \mathrm{w}_J)] = 0$;$\mathrm{E}[\mathrm{w_j}|(x_1, \mathrm{w}_1), (x_2, \mathrm{w}_2), \ldots, (x_J, \mathrm{w}_J)] = 0$. Of course, we can note that price or quantity are not included in the conditioning vector since they are partially determined by ξ_j and $\mathrm{w_j}$. We assume that product characteristics x_1 and cost shifters ω_j are exogenous.

Estimation Algorithm
Inverting the demand equations gives:

$$\delta_j(s^{obs}, \delta) = x_j\beta - \alpha p_j + \xi_j \qquad \textbf{\textit{(11)}}$$

Suppose Hj(x,w) is a matrix of instruments

$$E\left[H_j(x,w)\begin{pmatrix}\xi_j(s,\theta)\\ w_j(s,\theta)\end{pmatrix}\right] = 0 \qquad \textbf{\textit{(12)}}$$

Our goal is here to estimate the demand parameters α, β, γ, and θ. α_i is the consumer i's a marginal utility from income and β_{ijm} are demand parameters or individual-specific taste coefficients (for individual i purchasing j in market m). The moment conditions are:

$$E\left[H_j(x,w)\begin{pmatrix}\delta_j(s,\theta) - x_j\beta + \alpha p\\ P_j - c_j(q_j, w_j) - \frac{1}{\alpha}\left[\frac{s_j}{\partial s_j/\partial \delta_j}\right]\end{pmatrix}\right] = 0 \qquad \textbf{\textit{(13)}}$$

We carry out the estimation as a nested procedure: First, we make an outer loop for searching the minimum of the GMM objective function in the parameter space. The linear parameters α, β, and γ are easy to obtain using matrix algebra while estimating the nonlinear ones' numerical methods. Second, we make an inner loop for each θ, use contraction mapping to solve for δ_j.

4.2.2 Instruments

We use instrumental variables to deal with the endogeneity of prices and the classic problem faced when estimating demand models. Since price and other explanatory variables are correlated, we cannot capture the model's variances in demand parameters. We usually assume that these parameters in the model are a function of consumers' perceptions about the product, which vary by country, time, and demographics. This heterogeneity cause differences in the demand system and prices per period and market. Therefore, we need to find instruments for both the demand and pricing equations. Any variables correlated with prices and explanatory variables and not correlated with the demand market share are appropriate instruments. The next step is specifying a list of mean independent variables relevant to the variables to be instrumented. The unobservables for both supply and demand are mean independent of both observed product characteristics and cost shifters. (Nevo, 2000) summarizes some of the literature's solutions and suggests many types of instruments used in this setup. We use the same approach to select adequate instrumental variables. The instrumental variables must be associated with a corresponding product j and include all other products' characteristics and cost shifters. Finally, we test the validity of the instrumental variables. To obtain consistent parameter estimates, tests of overidentifying restrictions should inform about their reality (non-correlation with the error term). The tests' value does not reject the null that the instruments are valid in any of the estimated specifications.

Supply-side: Cost Data (w, supply shifters)

The first suggestion for demand-side instrumental variables (Nevo, 2000) is to look for uncorrelated variables with the demand shock and shift cost. Since most products do not come from European countries, the wage-setting process affects only the cost's marketing and logistic parts. For the demand for a specific brand and model, we need to find more model-specific information. It is quite challenging to obtain cost-related data because they are often confidential. We refer to some public data found on two major brands (Apple and Samsung) extrapolated by disassembling parts and adding up costs with a reasonable hypothesis (see https://www.fairphone.com or http://gizmodo.com). Some other independent organizations perform cost analysis based on this kind of reverse-engineering. Table 6 shows the results of this kind of research. The other nine countries (excluding the country to be instrumented) will be uncorrelated with market-specific valuation while controlling brand and demographics.

Table 6. Examples of production costs, retail prices, and margins

Smartphone	Production Cost	Retail Price	Profit margin (%)
Apple iPhone 7 (32GB)	$224.80	$649.00	65.4
Apple iPhone 6S Plus (16GB)	$236.00	$749.00	68.5
Apple iPhone 6S Plus (64GB)	$253.00	$849.00	70.2
Apple iPhone 6S (16GB)	$211.50	$649.00	67.4
Apple iPhone 6 Plus (16GB)	$215.60	$749.00	71.2
Apple iPhone 6 Plus (128GB)	$263.00	$949.00	72.4
Apple iPhone 6 (16GB)	$200.10	$649.00	69.2
Apple iPhone 6 (128GB)	$247.00	$849.00	70.9
Apple iPhone 5C (16GB)	$183.00	$549.00	67.0
Apple iPhone 5S (16GB)	$199.00	$649.00	69.0
Apple iPhone 5S (64GB)	$218.00	$849.00	74.0
Apple iPhone 5 (16GB)	$207.00	$649.00	68.0
Apple iPhone 4 (16GB)	$188.00	$599.00	69.0
Apple iPhone 4S (16GB)	$188.00	$599.00	69.0
Google Pixel XL (32GB)	$285.75	$769.00	62.8
Samsung Galaxy Note 3 (32GB)	$232.50	$699.00	69.6
Samsung Galaxy S3 (16GB)	$213.00	$549.00	61.0
Samsung Galaxy S4 (16GB HSPA+)	$244.00	$579.00	58.0
Samsung Galaxy S5 (32GB)	$256.00	$569.00	55.0
Samsung Galaxy S6 (32GB)	$275.50	$699.99	60.6
Samsung Galaxy S6 Edge (64GB)	$290.45	$799.99	63.7
Samsung Galaxy S7 (32GB)	$255.00	$599.00	57.4
Samsung Galaxy S8 (64GB)	$307.50	$720.00	57.3

Manufacturer (Brand) dummies

The most popular identifying assumption used to deal with the above endogeneity problem is to assume that products' location in the characteristics space is exogenous or predetermined to reveal the consumers' valuation of the unobserved product characteristics. This assumption can be combined with a specific model of competition and functional-form assumptions to generate an implicit set of instrumental variables as in (Bresnahan, 1981), (Bresnahan, 1987), (Verboven, 2014). If a manufacturer (brand) b sets prices of its products, it will maximize its profit, therefore the markup. However, those mobile phones with many comparable phones cannot have high markups due to increased competition. Since b has better information about its own products' prices and markups, the own markups vis-à-vis those of competitors' products will be different. Therefore, the optimal brand dummies will distinguish between the characteristics of products produced by the same manufacturer versus the features of products manufactured by others. Let J_b denote the set of all products produced by the manufacturer (brand) b. The suggestion of BLP for the instruments of x_{jb} (the kth characteristic of product j by the manufacturer or brand b) are:

$$x_{jk}, \sum_{r \neq j, r \in J_b} x_{rk}, \sum_{r \notin J_b} x_{rk}$$

Hausman type instruments

Similarly, as in the seminal paper by (Hausman, et al., 1994), also mentioned and used in (Nevo, 2000), the notations and the model we describe here are in the same context. We mainly make the most of the panel data's nature and construct instruments for the price by averaging product j's price in other markets different from those studied. We make here an assumption of oligopolistic competition (not unrealistic for the mobile phone market). Controlling for brand-specific interceptions and demographics helps to identify a hypothesis, as country-specific product evaluations are independent of cities but allowed to correlate within a country over some time. Under this assumption, prices of the same brand in other countries are valid instruments. The average marginal cost connects the prices of brand j in two countries. However, due to the assumption of independence, they are not correlated with the product's market-specific customer perception.

Demographics and other instruments

Demographics are assumed exogenous given the source of information used. We also think that the products' location in the characteristics space is exogenous or predetermined to reveal the unobserved product characteristics' valuation. This assumption can be combined with a specific competition model and functional-form assumptions to generate an implicit set of instrumental variables (Bresnahan, 1981) (Bresnahan, 1987) predetermined in an econometric sense. This assumption can be combined with a specific competition model and functional-form assumptions to generate an implicit set of instrumental variables (Bresnahan, 1981), (Bresnahan, 1987). Below in Table 7, we summarize some combinations selected, which show relatively good performance.

Table 7. Some selected instruments

I1	I2	I3	I6	I7	I10	I11	I14
2nd Camera MP	**CPU-CORES**	**RAM IN MB**	**Operating System**	**Keyboard**	**Bluetooth**	**Generation Total**	**NFC**
D1~D7 Brand dummies (8 Brands - 1)							

5. Results

We now report our findings for the model presented in Section 3 and applied it to the data described in Section 4. In Tables 12-13, we report the parameter estimates for various specifications. Due to big raw data and future consideration for the dynamic update, open-source statistic software R depends mainly on BLPestimatoR-package, though not exclusively. Moreover, to deal with BLP's weakness, the high dimensionality, we run most of the computation processes on Amazon Web Service(https://aws.amazon.com/), the state-of-the-art on-demand cloud computing platforms, and APIs.

The routine uses analytic gradients and offers a large number of implemented integration methods and optimization routines. We use a Wald test for goodness of fit. It tests whether the determinants explain the actual market shares. Table 8 provides some combinations selected for running the simulations (more details are in the Appendix). Here we only present product characteristics x1 to x5 (Display Size, 1st Camera Resolution, Subsidy, Storage in GB, and CPU) in addition to the price.[7] We also include interactions of these variables with demographics.

Table 8. Some selected combinations

Name	Price	x1	x2	x3	x4	x5
detail	Average selling price	Display Size	1st Camera Resolution	Subsidy	Storage IN GB	CPU
Type	endogenous	exogenous, random	exogenous, random	exogenous, random	exogenous, random	exogenous, random

5.1. Estimation without country dummies and demographics

We start with the simplest model, where we assume that countries are homogeneous, and there is no heterogeneity among individuals in a country. We summarize the parameter estimates for the RCL demand model given by equation (14) in Table 12 of the Appendix. As expected, the price parameter is negative and statistically significant, implying that higher prices reduce utility for mobile phone consumers. CPU partly captures the price effect, but the other included characteristics are non-significant. Price captures almost all the impact of mobile phone consumers' utility. The model and country dummy variables are, in general, highly significant. Once we include them, product characteristics do not affect consumers' utility. This result might be related to the considerable differences in tastes by brand and country. In case the flavors per market are different, we would expect improvement in our model's performance by introducing demographic information. We compare organic products to non-organic products in high brand effects as consumers are price-sensitive, so higher prices result in lower utility. These results suggest that average consumers are highly interested in specific brands, especially well-known brands. The market share's primary driver is brand-awareness (3-10 percent), which explains 1.4-1.6 percent of its market share.

5.2. Estimation with demographics

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[7] In many of the estimations with more than 5 variables, we do not get convergence of the GMM method or the results are meaningful at the optimum. We opt for choosing only 6 variables (price plus 5 product characteristics) entering linearly the utility function, out of the 21 possible explanatory variables (1 price + 20 product characteristics).

We show that it is possible to observe different consumer decisions in various countries with varying income levels and average age by relaxing homogeneity in tastes. We summarize the parameter estimates for the RCL demand model given by equation (14) in Table 13 of the Appendix. We estimate the distribution of marginal utilities by minimum-distance and present them in columns under the heading "Std. Error". The level of significance is shown next and grouped with different colors. On top of that, the parameter estimates for demographic variables allow calculating individual taste variations depending on them. The price Display Size, 1st Camera Resolution, Subsidy, Storage IN GB, and CPU enter the mean utility variation linearly and interact with demographics. Since all parameters are average values of the combination of parameters and demographics, we only discuss average impacts (i.e., effects around the mean).

At the aggregate level, we can make several observations. All brand dummy variables except for "branded" are non-statistically significant. This result might be because, on average, consumers do not show preferences for specific brands except in the case of Apple and Samsung. Moreover, country effects might be captured by country-level demographics, which should be observed by market and product level. Most of the intercepts are not significant, and this might be because of the large portion of "outside goods" since consumers buy a product in the generic group. The price parameter is negative and statistically significant, implying that higher prices reduce utility for mobile phone consumers. In general, as one might expect, being under the 19-year impact on the consumer's decisions negatively and make them heavily dependent on the price of the product. However, when a young consumer decides to purchase, he first considers the camera's resolution as a relevant factor. Older consumers value other different characteristics of mobile phones. Income shows, as expected, a positive relationship with the purchase decision. The higher the income, the higher the utility that the consumer attains. However, the marginal impact of income decreases with increased age.

Now we discuss the estimates in conjunction with demographics. A general observation about all of these results: tastes about mobile phones vary hugely with the country and demographic factors. The results represent our natural expectation about price elasticity of everyday goods -average consumers prefer massive subsidy from phone manufacturers and telecommunication companies at the purchasing, and these subsidies boost sales-. However, some remarkable points -on average to high-income demographics are interacting more with these subsidies than low-income demographics- we think it is because high-income individuals buy relatively pricy phones. Therefore, the absolute amount per handset should be high. Coefficients on the interaction of price with demographics are significant, while the standard deviation estimate suggests that the demographics explain most heterogeneity. Underage and above-average-income consumers tend to be less price-sensitive. The rest of the estimates have some different interpretations per combinations of explanatory variables. Table 9 reports a summary of the effects (signs and significance).

Table 9. Signs of parameters and statistical significance

	Mean	Income	Age	Age under 18
Price	-	+	+	-*
Display Size	+	-*	+*	-*
1st Camera Resolution	+	-*	+*	-*
Subsidy	+	+*	-	-*
Storage IN GB	+	-*	+*	+*
CPU	+	+*	-*	+*
Apple/Samsung	+*	+*	+*	+*

*statistically significant; + positive correlation; - Negative correlation

We summarize the average values for the ten countries of own and cross-price elasticities based on equation (8) in Table 14. The model gives more than 345,000 values for each country (98^2 times 36 months). These results would allow manufacturers to develop a customized and complex strategy per market and model and allow policymakers to analyze substitution patterns per brand, period, and market. However, here, we will only mention some general findings from the full set of results. Firstly, we comment on own-price elasticities. The majority of them are negative, as expected, and they range from -19.13 to 1.27. It implies that mobile demand is elastic. This result is consistent with the BLP estimations for the differentiated demand results. Table 15 report the minimum, average, and maximum values of own-brand-price elasticities for the ten countries.

Most of them are negative, and the range of variation goes from -8.65 to 0.24. The major brands, Apple, Samsung, Sony, HTC, and LG, show high own-brand substitution patterns. In essence, it seems logical that a company with a high market share would also have its own-brand competition. However, for one of those brands in a country with higher substitution patterns, product managers must re-think their product portfolios, trying to avoid their own-cannibalization. Cross-price elasticities show interesting results. First, they show lower figures (in absolute value) than own-price elasticities, suggesting that consumers tend to have some degree of product and brand loyalty for mobile phones. On average, for all ten selected countries, demand for Apple's iPhone-16-Gb-LTE and iPhone-64Gb-LTE models tend to be more elastic than the rest of Apple products, with cross-price elasticities in the range 0.21-0.39. The implication would be that if Apple increases the price of iPhone-16-Gb-LTE and iPhone-64Gb-LTE by 1 percent, the other products, as mentioned above, will increase demand by 0.21-0.39 percent, the highest figure among all selected models. Apple's Iphone5-16Gb-LTE, Samsung's GalaxyS4-16G-LTE, GalaxyA7-16Gb-LTE, Sony's One-32Gb-LTE, Onem8S-16GB-LTE, Htc LUMIA1020-32Gb-LTE, and Lg D855-G3-32Gb-LTE have very low average cross-price elasticities (around 0). This result suggests that consumers are less sensitive to price changes in those products.

Due to the heterogeneity of markets, we would observe many of our estimation results' tremendous implications at a model/country level of aggregation. To give some idea of these implications without overwhelming the reader with details, we display them in Table 10 only for the illustrative examples of 14 models for a country (The Netherlands) and a month (January 2016). Also, in Tables 20-29, we provide country-level aggregation results for other countries. To show how we use these results, some comments about them follow. In almost all countries except the Czech Republic and Poland, Apple and Samsung exhibit high brand-own cross-price elasticities, implying many lines of products are cannibalizing themselves. For those brands, product characterization, different positioning models, and price differentiation within the brands would increase sales and profits in many European countries.

Furthermore, in France, OneM8-S16Gb-Lte had, on average, a positive own-price sensitivity (due to its low price), so even price increases lead to increasing demand (kind of Giffen good). In Germany, Apple and Samsung's cross-product elasticity (0.09 on average) is higher than in other countries (0.05 on average), a kind of income effect. In the Netherlands, Apple Iphone5S-16Gb-LTE faces high cross-product elasticities against 8 Samsung and 2 Htc products. In Spain, Sony and Htc models show very low cross-price elasticities (around 0), while Samsung's' GalaxyS4-16Gb-LTE and Sony's XperiaZ2-LTE have positive own-price elasticity ranging from 1.11 to 2.25. In Austria, Apple iPhone6-16-Gb-LTE and iPhoneS5-16-Gb-LTE face too high cross-product elasticities against 8 Samsung, 2 Sony, and 4 Htc products. However, almost all Samsung's cross-product elasticity versus all other Android phones (0.02 on average) shows this brand is almost the unique alternative to the iPhone for most consumers in this country. Galaxy-alpha-32Gb-850F-NFC-LTE, Galaxy-S4Active-16GB-I9295 -LTE, and ONE-32GB-NFC-LTE had, on average, a positive own-price sensitivity, so even price increases lead to increasing demand.

We can also provide some results by any variable as a country, time, brand, etc. We will conclude this section with an example (Table 10) of the price sensitivity distribution attending to the product's market share (choosing those with the highest market shares). Most of the coefficients are statistically significant. There are some implications for the firm's managers, at least when they decide to launch new products. They should examine the kind of competition they face, the possibilities for substituting products among consumers, or the sort of portfolio that would prevent cannibalization within a brand.

Moreover, we can characterize the different brand models as price-elastic or price-inelastic, and a possible strategy consists of focusing on increasing sales (and the market share) according to these elasticities. Managers can identify other essential characteristics of the product for the consumer choice regardless of its price. Of course, policy-makers also have implications concerning a country's monopolistic/oligopolistic status. This fact, together with additional information as production costs and marginal profits, could generate cases of dumping. It is policy-makers' responsibility to evaluate companies' pricing strategies and introduce regulations to correct market failures when necessary.

Table 10. Price elasticities among models with high market share (The Netherlands, January 2016)

Brand	Display Size	1st Camera Resolution	Storage IN GB	Screen Resolution HIG	Model	Sahre	IPHONE5S16	IPHONE616G	IPHONE664G	IPHONE4S8G	IPHONE5C8G	GALAXYSIII	GALAXYS416	GALAXYS516	GALAXYS632	GALAXYS4MI	GALAXYS5NE	GALAXYA316	NEXUS516BG
APPLE	4	7990	16	1136	IPHONE5S16	6.19%	-1.151	0.041	0.028	-0.022	-0.008	-0.010	0.038	0.010	0.011	-0.036	-0.019	-0.024	-0.007
APPLE	5	7990	16	1334	IPHONE616G	3.54%	0.079	-1.084	0.028	-0.022	-0.008	-0.010	0.038	0.011	0.011	-0.036	-0.019	-0.024	-0.007
APPLE	5	7990	64	1334	IPHONE664G	1.51%	0.079	0.041	-1.770	-0.022	-0.008	-0.010	0.038	0.011	0.011	-0.036	-0.019	-0.024	-0.007
APPLE	4	7990	8	960	IPHONE4S8G	6.19%	0.084	0.042	0.029	-0.024	-0.009	-0.010	0.036	0.010	0.010	-0.037	-0.017	-0.025	-0.007
APPLE	4	7990	8	1136	IPHONE5C8G	2.36%	0.081	0.041	0.028	0.317	-0.008	-0.010	0.037	0.010	0.011	-0.036	-0.019	-0.024	-0.007
SAMSUI	5	7990	16	1280	GALAXYSIII	2.70%	0.080	0.041	0.028	-0.022	0.325	-0.010	0.038	0.010	0.011	-0.036	-0.019	-0.024	-0.007
SAMSUI	5	12780	16	1920	GALAXYS416	6.33%	0.073	0.039	0.026	-0.020	-0.008	-0.009	-0.572	0.012	0.012	-0.034	-0.022	-0.022	-0.007
SAMSUI	5	15872	16	1920	GALAXYS516	2.47%	0.070	0.037	0.025	-0.019	-0.007	-0.009	0.041	-0.431	0.013	-0.033	-0.023	-0.022	-0.007
SAMSUI	5	15872	32	2560	GALAXYS632	2.62%	0.069	0.037	0.025	-0.019	-0.007	-0.009	0.041	0.012	-0.434	-0.032	-0.023	-0.022	-0.007
SAMSUI	4	7990	8	960	GALAXYS4MI	6.67%	0.079	0.041	0.028	0.022	0.008	0.010	-0.038	-0.011	-0.011	-0.486	0.019	0.024	0.007
SAMSUI	5	15872	16	1920	GALAXYS5NE	4.16%	0.068	0.036	0.025	0.019	0.007	0.009	-0.041	-0.012	-0.013	0.032	-0.471	0.021	0.007
SAMSUI	5	7990	16	960	GALAXYA316	2.27%	0.078	0.041	0.028	0.022	0.008	0.010	-0.038	-0.011	-0.011	0.036	0.020	-0.993	0.007
LG	5	7990	16	1920	NEXUS516BG	1.72%	0.078	0.041	0.028	0.022	0.008	0.010	-0.038	-0.011	-0.011	0.035	0.020	0.023	-0.408

6. Concluding remarks

This paper studied the demand for several EU countries' mobile industry using marketing and IO literature proposals. Our paper's methods and results are meaningful for many people related to the mobile industry or demand estimation, such as mobile phone markers or European policy-makers. We present logit and RCL following the BLP/Nevo methodology of discrete purchases from aggregate data. We base our specifications on the market's observations, microeconomic demographics, and aggregate market intelligence data. We made the most of these data from many sources to understand static models of demand in the mobile phone industry. We find that the methodology is computationally quite challenging. We used macroeconomic data matching the distributional assumption for fitting demographics in each country. Raw data was carefully analyzed, and we select data of 98 products in 12 European countries for 36 months. We made some assumptions for the Hausman type and supply-side information for building suitable instruments.

The RCL model reveals impressive results. Estimations without demographics show mobile phones in European countries, in general, are well sold if their prices are low. The results, including demographics, offer several different conclusions per country and demographics. However, they also imply that heterogeneity in tastes is significant for consumer behavior in the country-time-specific mobile phone industry. Results indicate that consumers are price and income-sensitive.

Moreover, the results suggest that age (both in number and under 18/not) is a crucial determinant of consumers' tastes. We presented some findings of our RCL demand model given equation (14) at the aggregate and market levels. In the setting of (Nevo, 2000), we also estimated price elasticities as a by-product of estimating demand parameters. We showed that our approach and analysis are interesting for product managers who should make product prices and portfolios and policy-makers, who should objectively evaluate the market's regulation.

Our approach's significant contribution is to provide a practical method for estimating price elasticities for demand systems involving many similar datasets using market intelligence data. The applications to other related electronics industry would be relatively simple (see (Aguirregabiria & Ho, 2012), considering the similarities in characteristics, perishable nature of selling prices, heterogeneous demand, and demographic differences in tastes. The literature shows that researchers and companies have used statistical techniques and random coefficient logit (RCL) models the estimating demand systems, using historical sales series as their primary source of data. The paper shows an excellent example of applying the classical BLP model with smart use of estimation and instrumental variable constraints while making the newest technologies such as Amazon Web Service cloud and the state-of-the-art BLPestimatoR-package. Other approaches are also making the latest technologies, such as demand forecasts using Machine Learning (ML), a buzz word these days. ML demand forecasts sometimes can show better quality results than traditional techniques (Xu, 2018). However, the ML models cannot replace the RCL model.

Nevertheless, it can be accompanied by BLP because BLP shows more energetic performances in many contexts (Badruddoza & Modhurima, 2019). Moreover, interpretability is one of our RCL models and structural models' essential advantages compared to machine learning. As we showed in Chapter 4 in our paper, RCL can extract useful information from aggregate data such as coefficients, the relationship among variables, and own/cross-product price elasticities.

7. Acknowledgments

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8. Appendix

Table 11. Selected models and some characteristics

Brand	Model	1st Camera Resolution (K Pixel)	2nd Camera MP	CPU-CORES	RAM IN MB	Storage IN GB	Resolution HIG
APPLE	IPHONE5S16GBLTE	7990	1.2	2	1024	16	1136
	IPHONE616GBNFCLTE	7990	1.2	2	1024	16	1334
	IPHONE4S16GB	7990	0.3	2	512	16	960
	IPHONE516GBLTE	7990	1.2	2	1024	16	1136
	IPHONE664GBNFCLTE	7990	1.2	2	1024	64	1334
	IPHONE416GB	5018	0.3	1	512	16	960
	IPHONE48GB	5039	0.3	1	512	8	960
	IPHONE5S32GBLTE	7990	1.2	2	1024	32	1136
	IPHONE4S8GB	7990	0.3	2	512	8	960
	IPHONE5C16GBLTE	7990	1.2	2	1024	16	1136
	IPHONE532GBLTE	7990	1.2	2	1024	32	1136
	IPHONE6PLUS16GBNFCLTE	7990	1.2	2	1024	16	1920
	IPHONE5C8GBLTE	7990	1.2	2	1024	8	1136
	IPHONE6PLUS64GBNFCLTE	7990	1.2	2	1024	64	1920
	IPHONE4S32GB	7990	0.3	2	512	32	960
	IPHONE6128GBNFCLTE	7990	1.2	2	1024	128	1334
	IPHONE5S64GBLTE	7990	1.2	2	1024	64	1136
	IPHONE564GBLTE	7990	1.2	2	1024	64	1136
	IPHONE6PLUS128GBNFCLTE	7990	1.2	2	1024	128	1920
	IPHONE4S64GB	7990	0.3	2	512	64	960
	IPHONE5C32GBLTE	7990	1.2	2	1024	32	1136
SAMSUNG	GALAXYSIII16GBI9300NFC	7990	1.9	4	1024	16	1280
	GALAXYS416GBI9505NFCLTE	12780	2	4	2048	16	1920
	GALAXYS516GBG900NFCLTE	15872	2	4	2048	16	1920
	GALAXYS632GBG920NFCLTE	15872	5	8	3072	32	2560
	GALAXYS4MINI8GBI9195NFCLTE	7990	2	2	1536	8	960
	GALAXYS6EDGE32GBG925FNFCLTE	15872	5	8	3072	32	2560
	GALAXYNOTE332GBN9005NFCLTE	12780	2	4	3072	32	1920
	GALAXYS5MINI16GBG800FNFCLTE	7990	2.1	4	1536	16	1280

	GALAXYNOTE4N91032GBNFCLTE	15872	3.7	4	3072	32	2560
	GALAXYNOTEII16GBN7100NFC	7990	1.9	4	2048	16	1280
	GALAXYA5A500FNFCLTE	12780	5	4	2048	16	1280
	GALAXYS5NEO16GBG903FNFCLTE	15872	5	8	2048	16	1920
	GALAXYNOTE16GBN7000	7990	2	2	1024	16	1280
	GALAXYA316GBA300FNFCLTE	7990	5	4	1536	16	960
	GALAXYS6EDGEPLUS32GBG928NFCLTE	15872	5	8	4096	32	2560
	GALAXYALPHA32GBG850FNFCLTE	11944	2.1	8	2048	32	1280
	GALAXYS6EDGE64GBG925NFCLTE	15872	5	8	3072	64	2560
	GALAXYS416GBI9515NFCLTE	12780	2	4	2048	16	1920
	GALAXYS664GBG920NFCLTE	15872	5	8	3072	64	2560
	GALAXYNOTE3NEON7505NFCLTE	7990	2	6	2048	16	1280
	GALAXYS4ACTIVE16GBI9295NFCLTE	7990	2	4	2048	16	1920
	GALAXYNOTEII16GBN7105NFCLTE	7990	1.9	4	2048	16	1280
	GALAXYNOTEEDGE32GBN915NFCLTE	15925	3.7	4	3072	32	2560
	GALAXYXCOVER3G388FNFCLTE	5039	2	4	1536	8	800
	GALAXYGRAND2G7105NFCLTE	7990	1.9	4	1536	8	720
	GALAXYMEGA6.38GBI9205LTE	7990	1.9	2	1536	8	720
	GALAXYGRANDDUOSI9082	7990	2	2	1024	8	800
	GALAXYA716GBA700NFCLTE	12780	5	8	2048	16	1920
	GALAXYS4ZOOM8GBC1010NFC	17818	1.9	2	1536	8	960
SONY	XPERIAZNFCLTE	12780	2.2	4	2048	16	1920
	XPERIAZ3NFCLTE	20656	2.2	4	3072	16	1920
	XPERIAZ3COMPACTD5803NFCLTE	20656	2.2	4	2048	16	1280
	XPERIAZ2NFCLTE	20656	2.2	4	3072	16	1920
	XPERIAZ1COMPACTD5503NFCLTE	20656	2	4	2048	16	1280
	XPERIASPNFCLTE	7990	0.3	2	1024	8	1280
	XPERIAM4AQUA8GB	12780	5	8	2048	8	1280
	XPERIATLT30PNFC	12780	1.3	2	1024	16	1280
	XPERIAT3D5103NFCLTE	7990	1.1	4	1024	8	1280
	XPERIAVNFCLTE	13129	0.3	2	1024	8	1280
	XPERIAZULTRA16GBNFCLTE	7990	2	4	2048	16	1920
HTC	ONE32GBNFCLTE	4086	2.1	4	2048	32	1920

	ONEM816GBNFCLTE	4086	5	4	2048	16	1920
	ONES	7990	0.3	2	1024	16	960
	ONEX32GBNFC	7990	1.3	4	1024	32	1280
	ONEMINILTE	4086	1.6	2	1024	16	1280
	ONEM932GBNFCLTE	20171	4	8	3072	32	1920
	ONEMINI2NFCLTE	12780	5	4	1024	16	1280
	DESIRE820LTE	12979	8	4	2048	16	1280
	ONEM8S16GBNFCLTE	12780	5	8	2048	16	1920
NOKIA	LUMIA920NFCLTE	7990	1.3	2	1024	32	1280
	LUMIA93032GBNFCLTE	18690	1.2	4	2048	32	1920
	LUMIA92516GBNFCLTE	7990	1.3	2	1024	16	1280
	LUMIA102032GBNFCLTE	41484	1.2	2	2048	32	1280
	LUMIA830NFCLTE	8580	0.9	4	1024	16	1280
	LUMIA1320LTE	5039	0.3	2	1024	8	1280
	LUMIA735NFCLTE	6621	5	4	1024	8	1280
LG	D855G316GBNFCLTE	12979	2.1	4	2048	16	2560
	D802G216GBNFCLTE	12780	2.1	4	2048	16	1920
	H815G432GBNFCLTE	15872	8	6	3072	32	2560
	NEXUS516BGNFCLTE	7990	1.3	4	2048	16	1920
	D722G3SNFCLTE	7990	1.3	4	1024	8	1280
	D855G332GBNFCLTE	12979	2.1	4	3072	32	2560
	E960NEXUS416GBNFC	7990	1.3	4	2048	16	1280
	E975OPTIMUSGNFC	12979	1.3	4	2048	32	1280
BLACKBERRY	BOLD9900NFC	5039	0	1	768	8	640
	Z10NFCLTE	7990	2	2	2048	16	1280
	Q10NFCLTE	7990	2	2	2048	16	720
	CLASSIC16GBNFCLTE	7990	2	2	2048	16	720
	Z30NFCLTE	7990	2	2	2048	16	1280
	LEAP16GBLTE	7990	2	2	2048	16	1280
	Q5NFCLTE	5039	2	2	2048	8	720
HUAWEI	P8LITE16GBDUALNFCLTE	12979	5	8	2048	16	1280
	P816GBNFCLTE	12979	8	8	3072	16	1920
	ASCENDG7NFCLTE	12979	5	4	2048	16	1280
	ASCENDP7LTE	12979	8	4	2048	16	1920

	ASCENDP68GB	7990	5	4	2048	8	1280
	ASCENDMATE716GBNFCLTE	12780	5	8	2048	16	1920

Table 12. Results in models without demographics

Variable	Estimate	Std. Error	Pr(>|t|)
price	-0.895	0.266	0.000
dummy1	-3.429	0.150	0.000
dummy2	-3.077	0.144	0.000
dummy3	-0.931	0.152	0.000
dummy4	-2.543	0.150	0.000
dummy5	-1.796	0.134	0.000
dummy6	-1.143	0.198	0.000
dummy7	-3.74	0.155	0.000
country1	-0.535	0.274	0.051
country2	-1.085	0.280	0.000
country3	-1.414	0.270	0.000
country4	0.895	0.266	0.000
country5	-1.236	0.271	0.000
country6	-0.190	0.281	0498
country7	-1.134	0.269	0.000
country8	-1.618	0.274	0.000
country9	-1.353	0.278	0.000
price	-141.842	6.338	0.000
Display Size	0.008	0.648	0991
1st Camera Resolution	168.144	1860.847	0928
Subsidy	5.207	25.945	0.841
Storage IN GB	1.268	0.256	0.000
CPU	436.439	26.611	0.000

Pr(>|t|)	Pr(>|t|)	Pr(>|t|)	Pr(>|t|)
0.2	0.1	0.05	0.01

Table 13. Results in models with demographics

	income			age			underage		
	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)
price	356.92	81.22	0.000	55.87	193.16	0.772	-412.86	118.22	0.000
Display Size	-0.42	0.20	0.037	1.30	0.50	0.009	-0.88	0.35	0.011
1st Camera Resolution	-7073.48	2712.37	0.009	12116.98	3778.99	0.001	-5043.53	1779.66	0.005
Subsidy	87.85	25.35	0.000	-35.22	64.16	0.583	-52.61	45.14	0.244
Storage IN GB	-192.27	94.03	0.004	141.87	68.82	0.039	50.39	27.00	0.0620
CPU	940.96	176.15	0.000	-1956.45	408.95	0.000	1015.47	413.76	0.014
Wald test: 626.8766 on 16 DF, p-value: 0.000									

Pr(>|t|)	Pr(>|t|)	Pr(>|t|)	Pr(>|t|)
0.2	0.1	0.05	0.01

Table 14. Own and cross-product elasticities (average for ten countries)

Product	Brand	Model1	IPHONE 5S16GB LTE	IPHONE 616GB NFCLTE	IPHONE 516GBL TE	IPHONE 664GB NFCLTE	IPHONE 5S32GB LTE	IPHONE 5C16GB LTE	IPHONE 532GBL TE	IPHONE IPHONE 6PLUS1 6GBNF CLTE	IPHONE 6PLUS6 4GBNF CLTE	IPHONE 6128GB NFCLTE	IPHONE 5S64GB LTE	IPHONE 564GBL TE	IPHONE 6PLUS1 28GBN FCLTE	IPHONE 4S64GB	IPHONE 5C32GB LTE	GALAXY S516GB G900NF CLTE	GALAXY S632GB G920NF CLTE	S6EDGE 32GBG 925FNF CLTE	NOTE3 32GBN 9005NF CLTE	NOTE4 N91032 GBNFCL TE	S6EDGE PLUS32 GBG92 8NFCLT	ALPHA3 2GBG8 50FNFC LTE	S6EDGE 64GBG 925NFC LTE	GALAXY S664GB G920NF CLTE	S4ACTI VE16GB I9295N FCLTE	NOTEE DGE32 GBN91 5NFCLT	GALAXY A716G BA700 NFCLTE	XPERIA Z3NFCL TE	XPERIA Z2NFCL TE	ONE32 GBNFCL TE	ONEM8 16GBN FCLTE	ONEM9 32GBN FCLTE	ONEM8 S16GB NFCLTE	LUMIA 93032G BNFCLT E	LUMIA 102032 GBNFCL TE	D855G 316GB NFCLTE	H815G 432GB NFCLTE	D855G 332GB NFCLTE	ASCEN DMATE 716GB NFCLTE
product01	APPLE	IPHONE5S16GBLTE	(6.37)	0.29	0.00	0.18	0.03	0.01	0.00	0.04	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.10	0.10	0.08	0.02	0.04	0.03	0.01	0.02	0.01	0.00	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product02	APPLE	IPHONE616GBNFCLTE	0.16	(9.10)	0.00	0.19	0.04	0.01	0.00	0.05	0.04	0.03	0.01	0.00	0.01	0.00	0.00	0.10	0.11	0.08	0.02	0.04	0.04	0.01	0.02	0.01	0.00	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product04	APPLE	IPHONE516GBLTE	0.14	0.24	(3.28)	0.15	0.03	0.01	0.00	0.04	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.09	0.09	0.07	0.02	0.03	0.03	0.00	0.01	0.01	0.00	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product05	APPLE	IPHONE664GBNFCLTE	0.14	0.26	0.00	(11.91)	0.05	0.01	0.00	0.04	0.07	0.07	0.02	0.00	0.03	0.00	0.00	0.08	0.11	0.08	0.02	0.04	0.04	0.01	0.03	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product08	APPLE	IPHONE5S32GBLTE	0.15	0.29	0.00	0.32	(8.79)	0.01	0.00	0.04	0.05	0.04	0.01	0.00	0.02	0.00	0.00	0.09	0.11	0.08	0.02	0.04	0.04	0.01	0.02	0.02	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product10	APPLE	IPHONE5C16GBLTE	0.14	0.23	0.00	0.15	0.03	(2.15)	0.00	0.04	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.10	0.09	0.07	0.02	0.03	0.03	0.00	0.01	0.01	0.00	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product11	APPLE	IPHONE532GBLTE	0.14	0.26	0.00	0.28	0.04	0.01	(4.53)	0.04	0.05	0.04	0.01	0.00	0.02	0.00	0.00	0.08	0.11	0.08	0.02	0.03	0.03	0.01	0.02	0.02	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product12	APPLE	IPHONE6PLUS16GBNFCLTE	0.15	0.30	0.00	0.18	0.03	0.01	0.00	(12.70)	0.04	0.02	0.01	0.00	0.01	0.00	0.00	0.10	0.13	0.10	0.02	0.05	0.04	0.01	0.02	0.02	0.00	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product14	APPLE	IPHONE6PLUS64GBNFCLTE	0.14	0.24	0.00	0.36	0.04	0.01	0.00	0.04	(15.86)	0.06	0.01	0.00	0.03	0.00	0.00	0.09	0.14	0.10	0.02	0.04	0.05	0.01	0.03	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product16	APPLE	IPHONE6128GBNFCLTE	0.13	0.22	0.00	0.52	0.05	0.01	0.00	0.03	0.09	(15.69)	0.02	0.00	0.06	0.00	0.00	0.07	0.11	0.08	0.02	0.03	0.04	0.01	0.03	0.03	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product17	APPLE	IPHONE5S64GBLTE	0.14	0.26	0.00	0.43	0.05	0.01	0.00	0.04	0.07	0.07	(11.92)	0.00	0.03	0.00	0.00	0.08	0.11	0.08	0.02	0.04	0.04	0.01	0.02	0.02	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product18	APPLE	IPHONE564GBLTE	0.13	0.23	0.00	0.41	0.04	0.01	0.00	0.03	0.07	0.08	0.02	(6.24)	0.04	0.00	0.00	0.07	0.11	0.08	0.02	0.03	0.04	0.01	0.03	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product19	APPLE	IPHONE6PLUS128GBNFCLTE	0.12	0.21	0.00	0.45	0.04	0.01	0.00	0.03	0.09	0.11	0.02	0.00	(19.13)	0.00	0.00	0.07	0.13	0.10	0.02	0.04	0.05	0.01	0.04	0.04	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product20	APPLE	IPHONE4S64GB	0.13	0.21	0.00	0.41	0.04	0.01	0.00	0.03	0.07	0.08	0.02	0.00	0.04	(2.28)	0.00	0.07	0.10	0.07	0.02	0.03	0.03	0.01	0.03	0.02	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product21	APPLE	IPHONE5C32GBLTE	0.13	0.24	0.00	0.32	0.04	0.01	0.00	0.04	0.05	0.05	0.01	0.00	0.02	0.00	(4.96)	0.08	0.11	0.08	0.02	0.03	0.04	0.01	0.02	0.02	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
product24	SAMSUNG	GALAXYS516GBG900NFCLTE	0.14	0.24	0.00	0.12	0.03	0.01	0.00	0.04	0.03	0.02	0.01	0.00	0.01	0.00	0.00	(3.54)	0.12	0.09	0.02	0.04	0.04	0.00	0.02	0.02	0.00	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.01	0.00	0.00
product25	SAMSUNG	GALAXYS632GBG920NFCLTE	0.13	0.22	0.00	0.18	0.03	0.01	0.00	0.04	0.04	0.03	0.01	0.00	0.02	0.00	0.00	0.09	(6.79)	0.15	0.02	0.07	0.07	0.00	0.03	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.02	0.00	0.00
product27	SAMSUNG	GALAXYS6EDGE32GBG925FNFCLTE	0.14	0.24	0.00	0.18	0.03	0.01	0.00	0.05	0.04	0.03	0.01	0.00	0.01	0.00	0.00	0.09	0.20	(11.45)	0.02	0.06	0.07	0.00	0.03	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.02	0.00	0.00
product28	SAMSUNG	GALAXYNOTE332GBN9005NFCLTE	0.13	0.22	0.00	0.19	0.03	0.01	0.00	0.04	0.04	0.03	0.01	0.00	0.02	0.00	0.00	0.09	0.18	0.12	(3.24)	0.05	0.06	0.00	0.03	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.02	0.00	0.00
product30	SAMSUNG	GALAXYNOTE4N91032GBNFCLTE	0.14	0.24	0.00	0.17	0.03	0.01	0.00	0.05	0.04	0.03	0.01	0.00	0.01	0.00	0.00	0.09	0.20	0.14	0.02	(8.29)	0.07	0.01	0.03	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.02	0.00	0.00
product36	SAMSUNG	GALAXYS6EDGEPLUS32GBG928NFCLTE	0.13	0.23	0.00	0.19	0.03	0.01	0.00	0.05	0.05	0.03	0.01	0.00	0.02	0.00	0.00	0.09	0.21	0.15	0.02	0.06	(11.86)	0.00	0.03	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.02	0.00	0.00
product37	SAMSUNG	GALAXYALPHA32GBG850FNFCLTE	0.13	0.23	0.00	0.25	0.03	0.01	0.00	0.04	0.05	0.04	0.01	0.00	0.02	0.00	0.00	0.08	0.11	0.08	0.02	0.04	0.04	(1.45)	0.02	0.02	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
product38	SAMSUNG	GALAXYS6EDGE64GBG925NFCLTE	0.13	0.22	0.00	0.25	0.03	0.01	0.00	0.04	0.06	0.05	0.01	0.00	0.03	0.00	0.00	0.09	0.20	0.15	0.02	0.06	0.07	0.01	(14.33)	0.04	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.02	0.00	0.00
product40	SAMSUNG	GALAXYS664GBG920NFCLTE	0.13	0.20	0.00	0.25	0.03	0.01	0.00	0.04	0.06	0.05	0.01	0.00	0.03	0.00	0.00	0.08	0.21	0.15	0.02	0.06	0.07	0.01	0.04	(10.25)	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.02	0.00	0.00
product42	SAMSUNG	GALAXYS4ACTIVE16GBI9295NFCLTE	0.12	0.17	0.00	0.11	0.02	0.01	0.00	0.03	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.08	0.11	0.08	0.01	0.04	0.04	0.00	0.02	0.02	1.27	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.01	0.00	0.00
product44	SAMSUNG	GALAXYNOTEEDGE32GBN915NFCLTE	0.14	0.24	0.00	0.18	0.03	0.01	0.00	0.05	0.05	0.03	0.01	0.00	0.01	0.00	0.00	0.09	0.20	0.15	0.02	0.06	0.07	0.00	0.03	0.03	0.00	(12.81)	0.00	0.02	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.02	0.00	0.00
product49	SAMSUNG	GALAXYA716GBA700NFCLTE	0.12	0.20	0.00	0.15	0.03	0.01	0.00	0.04	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.08	0.14	0.10	0.02	0.04	0.05	0.00	0.02	0.02	0.00	0.01	(0.62)	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.01	0.00	0.00
product52	SONY	XPERIAZ3NFCLTE	0.14	0.24	0.00	0.12	0.02	0.01	0.00	0.04	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.10	0.11	0.08	0.02	0.04	0.04	0.00	0.02	0.02	(0.00)	0.01	0.00	(4.86)	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.01	0.00	0.00
product54	SONY	XPERIAZ2NFCLTE	0.13	0.21	0.00	0.10	0.02	0.02	0.00	0.03	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.11	0.10	0.07	0.02	0.03	0.03	0.00	0.01	0.01	0.00	0.01	0.00	0.02	(1.70)	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.01	0.00	0.00
product62	HTC	ONE32GBNFCLTE	0.12	0.18	0.00	0.16	0.03	0.01	0.00	0.03	0.04	0.03	0.01	0.00	0.02	0.00	0.00	0.08	0.17	0.11	0.02	0.05	0.05	0.00	0.03	0.03	0.00	0.01	0.00	0.02	0.01	0.82	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.02	0.00	0.00
product63	HTC	ONEM816GBNFCLTE	0.14	0.24	0.00	0.13	0.03	0.02	0.00	0.04	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.11	0.12	0.09	0.02	0.04	0.04	0.00	0.02	0.02	0.00	0.01	0.00	0.02	0.01	0.00	(4.57)	0.01	0.00	(0.00)	0.00	(0.00)	0.01	0.00	0.00
product67	HTC	ONEM932GBNFCLTE	0.14	0.26	0.00	0.19	0.03	0.01	0.00	0.05	0.04	0.03	0.01	0.00	0.02	0.00	0.00	0.09	0.15	0.12	0.02	0.05	0.05	0.01	0.03	0.02	0.00	0.01	0.00	0.02	0.01	0.00	0.01	(8.39)	0.00	(0.00)	0.00	(0.00)	0.01	0.00	0.00
product70	HTC	ONEM8S16GBNFCLTE	0.12	0.21	0.00	0.10	0.02	0.01	0.00	0.04	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.09	0.10	0.08	0.01	0.03	0.03	0.00	0.01	0.01	0.00	0.01	0.00	0.03	0.01	0.00	0.01	0.01	(2.12)	(0.00)	0.00	(0.00)	0.01	0.00	0.00
product72	NOKIA	LUMIA93032GBNFCLTE	0.12	0.18	0.00	0.16	0.03	0.01	0.00	0.03	0.04	0.03	0.01	0.00	0.02	0.00	0.00	0.09	0.18	0.12	0.02	0.05	0.06	0.00	0.03	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.40)	0.00	(0.00)	0.02	0.00	0.00
product74	NOKIA	LUMIA102032GBNFCLTE	0.12	0.20	0.00	0.21	0.03	0.01	0.00	0.03	0.04	0.03	0.01	0.00	0.02	0.00	0.00	0.07	0.11	0.08	0.02	0.03	0.04	0.00	0.02	0.02	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.89	(0.00)	0.01	0.00	0.00
product78	LG	D855G316GBNFCLTE	0.12	0.19	0.00	0.11	0.02	0.01	0.00	0.03	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.09	0.16	0.11	0.02	0.05	0.05	0.00	0.02	0.02	(0.00)	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	0.10	0.02	0.00	0.00
product80	LG	H815G432GBNFCLTE	0.13	0.21	0.00	0.18	0.03	0.01	0.00	0.04	0.04	0.03	0.01	0.00	0.02	0.00	0.00	0.09	0.22	0.15	0.02	0.07	0.07	0.00	0.03	0.04	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	(3.83)	0.00	0.00
product83	LG	D855G332GBNFCLTE	0.12	0.18	0.00	0.17	0.03	0.01	0.00	0.04	0.04	0.03	0.01	0.00	0.02	0.00	0.00	0.08	0.23	0.15	0.02	0.07	0.07	0.00	0.03	0.04	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.03	(1.17)	0.00
product98	HUAWEI	ASCENDMATE716GBNFCLTE	0.12	0.21	0.00	0.15	0.03	0.01	0.00	0.04	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.08	0.13	0.09	0.02	0.04	0.04	0.00	0.02	0.02	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.01	0.00	(0.90)

Table 15. Brand own-price elasticities - statistics for ten countries

Country	Stat	Apple	Samsung	Sony	HTC	Nokia	LG	Huawei
Average	Min	-19.13	-14.33	-4.86	-8.39	-0.40	-3.83	-0.90

	Max	-2.15	1.27	-1.70	0.82	0.89	0.10	-0.90
	Avg	-2.88	-2.32	-1.09	-1.19	0.24	-1.63	-0.90
France	Min	-19.67	-14.93	-6.70	-8.92	-1.30	-4.59	-1.83
	Max	1.59	-0.07	-3.72	0.65	-1.07	-1.79	-1.83
	Avg	-2.97	-2.64	-1.74	-1.31	-1.18	-2.80	-1.83
Germany	Min	-17.50	-14.79	-3.61	-7.68	0.39	-4.22	0.74
	Max	-1.24	2.94	-0.24	1.89	2.71	1.13	0.74
	Avg	-2.70	-1.98	-0.64	-0.65	1.55	-1.15	0.74
Spain	Min	-19.52	-14.08	-5.94	-10.76	-0.20	-6.08	-1.27
	Max	-2.70	1.11	-3.24	2.25	-0.04	-0.39	-1.27
	Avg	-3.05	-2.32	-1.53	-1.24	-0.12	-2.67	-1.27
Italy	Min	-20.32	-17.45	-3.64	-8.75	-1.24	-5.58	-2.41
	Max	-3.51	0.17	-1.42	-1.79	-0.90	-0.85	-2.41
	Avg	-3.37	-3.01	-0.84	-1.94	-1.07	-2.72	-2.41
Austria	Min	-17.18	-12.87	-3.64	-6.39	0.20	-1.99	0.74
	Max	-1.45	0.27	-0.29	0.40	1.12	0.83	0.74
	Avg	-2.59	-1.96	-0.65	-0.74	0.66	-0.45	0.74
Belgium	Min	-18.56	-13.34	-4.71	-9.39	0.25	-2.93	-0.75
	Max	-0.98	0.32	-1.38	1.25	2.35	-0.90	-0.75
	Avg	-2.85	-2.30	-1.01	-1.14	1.30	-2.04	-0.75
Czech Republic	Min	-19.28	-15.65	-6.67	-8.18	-0.30	-2.02	-1.50
	Max	-1.06	1.95	-0.65	1.52	1.34	2.33	-1.50
	Avg	-2.59	-2.50	-1.22	-1.29	0.52	-0.24	-1.50
Netherlands	Min	-18.69	-12.41	-3.28	-7.69	0.07	-3.45	-0.39
	Max	-0.57	2.21	-0.93	1.75	1.21	0.54	-0.39
	Avg	-2.65	-1.98	-0.70	-0.79	0.64	-1.04	-0.39
Poland	Min	-20.35	-13.18	-4.73	-9.04	-0.61	-3.36	-0.98
	Max	-1.20	3.25	-1.64	2.20	2.22	1.80	-0.98
	Avg	-3.11	-1.88	-1.06	-1.66	0.81	-0.88	-0.98
Portugal	Min	-20.21	-14.72	-5.73	-7.35	-1.86	-4.68	-1.40
	Max	0.23	0.55	-3.48	0.90	0.48	-0.85	-1.40
	Avg	-2.95	-2.59	-1.53	-1.12	-0.69	-2.34	-1.40

Table 16. Number of products per brand and pricing group

12 Brand	(Multiple Items)				
Count of Model	Tier				
Brand	Basic	Step-Up	High	Premium	Grand Total
ALCATEL	398	48	14		460
APPLE	14	21	26	38	99
BLACKBERRY	56	55	36	29	176
HTC	150	152	119	79	500
HUAWEI	162	78	39	32	311
LG	371	142	62	44	619
MICROSOFT	21	10	1	7	39
MOTOROLA	212	78	60	35	385
NOKIA	407	181	84	46	718
SAMSUNG	783	368	190	138	1479
SONY	245	156	79	52	532
WIKO	89	27	4		120
Grand Total	**2908**	**1316**	**714**	**500**	**5438**

Table 17. Development of Shares of Tiers

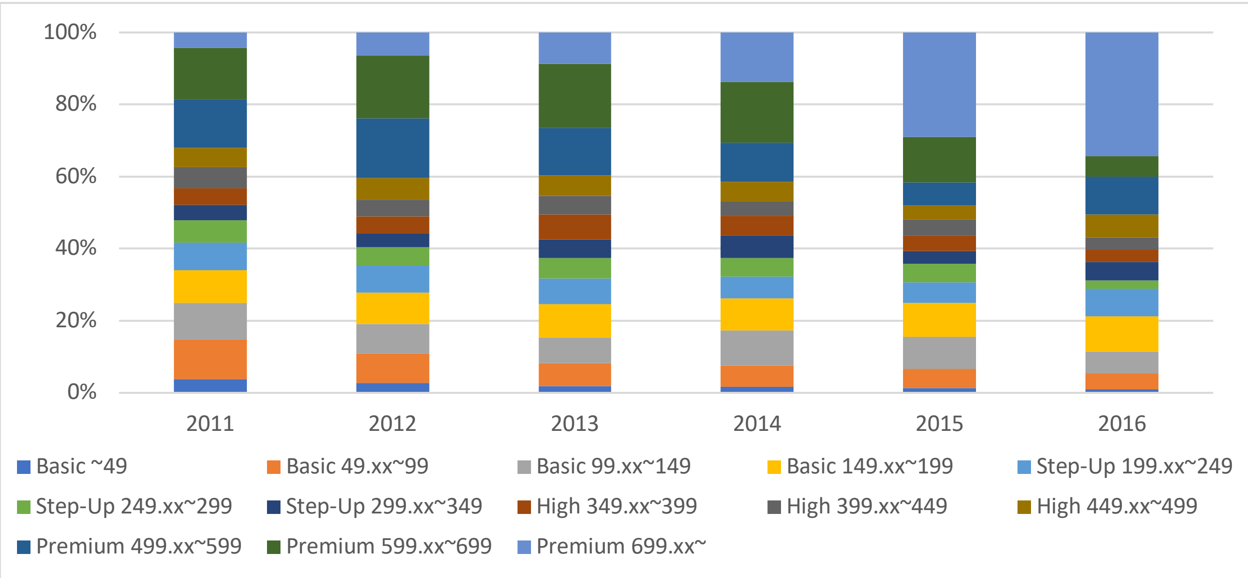

Table 18. Average Sales Price of handsets in Europe (IDC)

Country	2011	2012	2013	2014	2015	2016	GrandTotal
Austria	128	163	161	181	215	212	171
Belgium	148	176	217	234	263		206
Czechia	134	136	147	148	173	192	150
France	86	115	140	153	169	169	134
Germany	114	139	170	172	198	204	159
Italy	131	162	172	191	218	242	176
Netherlands	232	251	288	310	344	356	286
Poland	27	40	51	73	94	103	59
Portugal	88	104	144	159	174	191	137
Spain	75	94	114	115	144	155	107
Switzerland	167	170					168
Average	**107**	**131**	**153**	**163**	**187**	**196**	**149**
ASP Growth rate		23%	17%	7%	14%	5%	13%

Table 19 Number of Brands per pricing group in Europe (GfK)

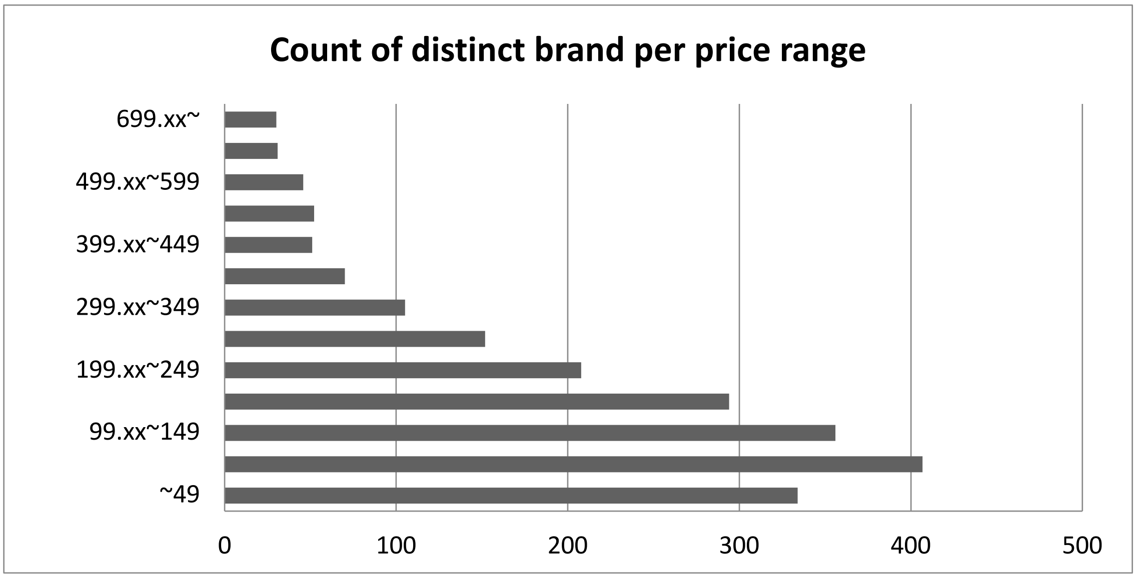

Table 20 Cross product-price elasticities of some products, Italy

		cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI
		Min	(20.32)		Min	(20.32)	Min	(17.45)	Min	(3.64)	Min	(8.75)	Min	(1.24)	Min	(5.58)	Min	(2.41)
		Max	0.17		Max	(3.51)	Max	0.17	Max	(1.42)	Max	(1.79)	Max	(0.90)	Max	(0.85)	Max	(2.41)
		Avg	(8.65)		Avg	(10.11)	Avg	(9.04)	Avg	(2.53)	Avg	(5.81)	Avg	(1.07)	Avg	(2.72)	Avg	(2.41)
All	Italy	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20
Min	(20.32)	product01	APPLE	IPHONE5S	(7.81)	0.28	0.00	0.32	0.03	0.02	0.00	0.05	0.04	0.01	0.01	0.00	0.01	0.00
Max	0.79	product02	APPLE	IPHONE61	0.12	(10.33)	0.00	0.19	0.02	0.02	0.00	0.06	0.03	0.01	0.00	0.00	0.00	0.00
Avg	(0.17)	product04	APPLE	IPHONE51	0.11	0.26	(3.91)	0.25	0.02	0.02	0.00	0.05	0.04	0.02	0.01	0.00	0.01	0.00
		product05	APPLE	IPHONE66	0.11	0.22	0.00	(12.82)	0.03	0.02	0.00	0.04	0.11	0.08	0.01	0.00	0.03	0.00
		product08	APPLE	IPHONE5S	0.12	0.25	0.00	0.54	(10.44)	0.02	0.00	0.04	0.07	0.03	0.01	0.00	0.01	0.00
		product10	APPLE	IPHONE5C	0.11	0.24	0.00	0.25	0.02	(3.51)	0.00	0.04	0.04	0.02	0.01	0.00	0.01	0.00
		product11	APPLE	IPHONE53	0.10	0.20	0.00	0.48	0.03	0.02	(5.44)	0.03	0.07	0.05	0.01	0.00	0.02	0.00
		product12	APPLE	IPHONE6P	0.12	0.32	0.00	0.17	0.02	0.02	0.00	(14.06)	0.03	0.00	0.00	0.00	0.00	0.00
		product14	APPLE	IPHONE6P	0.10	0.20	0.00	0.58	0.03	0.02	0.00	0.04	(17.24)	0.08	0.01	0.00	0.03	0.00
		product16	APPLE	IPHONE61	0.04	0.10	0.00	0.79	0.02	0.00	0.00	0.01	0.13	(17.34)	0.01	0.00	0.08	0.00
		product17	APPLE	IPHONE5S	0.12	0.22	0.00	0.57	0.03	0.02	0.00	0.04	0.07	0.06	(12.84)	0.00	0.03	0.00
		product18	APPLE	IPHONE56	0.06	0.11	0.00	0.68	0.02	0.01	0.00	0.02	0.11	0.15	0.01	(9.44)	0.07	0.00
		product19	APPLE	IPHONE6P	0.03	0.08	0.00	0.66	0.02	0.00	0.00	0.01	0.13	0.18	0.01	0.00	(20.32)	0.00
		product20	APPLE	IPHONE4S	0.03	0.08	0.00	0.65	0.02	0.00	0.00	0.01	0.10	0.16	0.01	0.00	0.07	(4.02)
		product21	APPLE	IPHONE5C	0.09	0.19	0.00	0.48	0.03	0.01	0.00	0.03	0.07	0.05	0.01	0.00	0.02	0.00
		product24	SAMSUNG	GALAXYS5	0.11	0.31	0.00	0.14	0.02	0.02	0.00	0.06	0.03	0.00	0.00	0.00	0.00	0.00
		product25	SAMSUNG	GALAXYS6	0.11	0.22	0.00	0.18	0.02	0.02	0.00	0.04	0.04	0.01	0.01	0.00	0.01	0.00
		product27	SAMSUNG	GALAXYS6	0.11	0.23	0.00	0.20	0.02	0.02	0.00	0.05	0.05	0.01	0.01	0.00	0.01	0.00
		product28	SAMSUNG	GALAXYN(	0.11	0.21	0.00	0.19	0.02	0.02	0.00	0.04	0.04	0.01	0.00	0.00	0.01	0.00
		product30	SAMSUNG	GALAXYN(	0.11	0.23	0.00	0.19	0.02	0.02	0.00	0.05	0.04	0.01	0.00	0.00	0.01	0.00
		product36	SAMSUNG	GALAXYS6	0.11	0.23	0.00	0.19	0.02	0.02	0.00	0.05	0.04	0.01	0.00	0.00	0.01	0.00
		product37	SAMSUNG	GALAXYAL	0.09	0.22	0.00	0.36	0.02	0.01	0.00	0.04	0.05	0.02	0.01	0.00	0.01	0.00
		product38	SAMSUNG	GALAXYS6	0.09	0.16	0.00	0.30	0.02	0.01	0.00	0.03	0.08	0.06	0.01	0.00	0.03	0.00
		product40	SAMSUNG	GALAXYS6	0.10	0.19	0.00	0.23	0.02	0.02	0.00	0.04	0.06	0.03	0.01	0.00	0.02	0.00
		product42	SAMSUNG	GALAXYS4	0.09	0.20	0.00	0.12	0.02	0.02	0.00	0.04	0.03	0.01	0.00	0.00	0.01	0.00
		product44	SAMSUNG	GALAXYN(	0.11	0.22	0.00	0.20	0.02	0.02	0.00	0.05	0.05	0.01	0.00	0.00	0.01	0.00
		product49	SAMSUNG	GALAXYA7	0.07	0.22	0.00	0.15	0.02	0.01	0.00	0.04	0.03	0.02	0.00	0.00	0.01	0.00
		product52	SONY	XPERIAZ3I	0.09	0.26	0.00	0.15	0.02	0.02	0.00	0.05	0.03	0.01	0.00	0.00	0.01	0.00
		product54	SONY	XPERIAZ2I	0.10	0.26	0.00	0.12	0.02	0.02	0.00	0.05	0.02	0.01	0.00	0.00	0.00	0.00
		product62	HTC	ONE32GBI	0.09	0.19	0.00	0.17	0.02	0.02	0.00	0.04	0.04	0.02	0.00	0.00	0.01	0.00
		product63	HTC	ONEM816	0.11	0.24	0.00	0.16	0.02	0.02	0.00	0.05	0.03	0.01	0.00	0.00	0.01	0.00
		product67	HTC	ONEM932	0.10	0.21	0.00	0.27	0.02	0.02	0.00	0.04	0.06	0.02	0.00	0.00	0.01	0.00
		product70	HTC	ONEM8S1	0.11	0.32	0.00	0.15	0.02	0.02	0.00	0.06	0.03	0.00	0.00	0.00	0.00	0.00
		product72	NOKIA	LUMIA930	0.07	0.16	0.00	0.17	0.02	0.01	0.00	0.03	0.04	0.02	0.00	0.00	0.01	0.00
		product74	NOKIA	LUMIA102	0.11	0.19	0.00	0.26	0.02	0.02	0.00	0.04	0.04	0.02	0.01	0.00	0.01	0.00
		product78	LG	D855G316	0.09	0.22	0.00	0.12	0.02	0.02	0.00	0.04	0.03	0.01	0.00	0.00	0.00	0.00
		product80	LG	H815G432	0.09	0.20	0.00	0.17	0.02	0.02	0.00	0.04	0.04	0.01	0.00	0.00	0.01	0.00
		product83	LG	D855G332	0.07	0.18	0.00	0.15	0.02	0.01	0.00	0.04	0.03	0.01	0.00	0.00	0.01	0.00
		product98	HUAWEI	ASCENDM	0.09	0.26	0.00	0.16	0.02	0.02	0.00	0.05	0.03	0.01	0.00	0.00	0.01	0.00

Table 21 Cross product-price elasticities of some products, the Netherlands

		cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI	
		Min	(18.69)		Min	(18.69)	Min	(12.41)	Min	(3.28)	Min	(7.69)	Min	0.07	Min	(3.45)	Min	(0.39)
		Max	2.21		Max	(0.57)	Max	2.21	Max	(0.93)	Max	1.75	Max	1.21	Max	0.54	Max	(0.39)
		Avg	(6.14)		Avg	(7.96)	Avg	(5.93)	Avg	(2.10)	Avg	(2.38)	Avg	0.64	Avg	(1.04)	Avg	(0.39)
All	Netherlands	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20
Min	(18.69)	product01	APPLE	IPHONE5S	(5.54)	0.66	0.00	0.42	0.07	0.02	0.00	0.08	0.08	0.03	0.01	0.00	0.02	0.00
Max	2.21	product02	APPLE	IPHONE61	0.39	(7.04)	0.00	0.45	0.08	0.02	0.00	0.09	0.09	0.04	0.01	0.00	0.02	0.00
Avg	(0.08)	product04	APPLE	IPHONE51	0.31	0.47	(7.10)	0.26	0.05	0.02	0.00	0.06	0.06	0.02	0.01	0.00	0.01	0.00
		product05	APPLE	IPHONE66	0.40	0.77	0.00	(11.36)	0.09	0.02	0.00	0.09	0.12	0.06	0.01	0.00	0.03	0.00
		product08	APPLE	IPHONE5S	0.42	0.81	0.00	0.57	(7.58)	0.02	0.00	0.09	0.10	0.05	0.01	0.00	0.02	0.00
		product10	APPLE	IPHONE5C	0.30	0.44	0.00	0.25	0.05	(0.57)	0.00	0.06	0.05	0.02	0.01	0.00	0.01	0.00
		product11	APPLE	IPHONE53	0.37	0.70	0.00	0.47	0.08	0.02	(3.60)	0.09	0.09	0.04	0.01	0.00	0.02	0.00
		product12	APPLE	IPHONE6P	0.35	0.62	0.00	0.40	0.06	0.02	0.00	(11.84)	0.09	0.03	0.01	0.00	0.02	0.00
		product14	APPLE	IPHONE6P	0.35	0.65	0.00	0.53	0.07	0.02	0.00	0.10	(15.24)	0.05	0.01	0.00	0.03	0.00
		product16	APPLE	IPHONE61	0.36	0.66	0.00	0.76	0.09	0.02	0.00	0.09	0.14	(14.97)	0.01	0.00	0.05	0.00
		product17	APPLE	IPHONE5S	0.41	0.76	0.00	0.65	0.09	0.02	0.00	0.09	0.11	0.07	(10.23)	0.00	0.03	0.00
		product18	APPLE	IPHONE56	0.37	0.69	0.00	0.58	0.08	0.02	0.00	0.09	0.11	0.06	0.01	(5.23)	0.03	0.00
		product19	APPLE	IPHONE6P	0.34	0.60	0.00	0.66	0.08	0.02	0.00	0.09	0.15	0.09	0.01	0.00	(18.69)	0.00
		product20	APPLE	IPHONE4S	0.34	0.61	0.00	0.54	0.08	0.02	0.00	0.07	0.09	0.06	0.01	0.00	0.03	(1.06)
		product21	APPLE	IPHONE5C	0.39	0.72	0.00	0.50	0.08	0.02	0.00	0.09	0.09	0.04	0.01	0.00	0.02	0.00
		product24	SAMSUNG	GALAXYS5	0.29	0.45	0.00	0.26	0.04	0.02	0.00	0.08	0.07	0.03	0.01	0.00	0.01	0.00
		product25	SAMSUNG	GALAXYS6	0.30	0.47	0.00	0.32	0.05	0.02	0.00	0.10	0.09	0.03	0.01	0.00	0.02	0.00
		product27	SAMSUNG	GALAXYS6	0.31	0.49	0.00	0.33	0.05	0.02	0.00	0.10	0.10	0.03	0.01	0.00	0.02	0.00
		product28	SAMSUNG	GALAXYN(	0.31	0.49	0.00	0.33	0.06	0.02	0.00	0.09	0.09	0.03	0.01	0.00	0.02	0.00
		product30	SAMSUNG	GALAXYN(	0.31	0.48	0.00	0.32	0.05	0.02	0.00	0.10	0.10	0.03	0.01	0.00	0.02	0.00
		product36	SAMSUNG	GALAXYS6	0.32	0.50	0.00	0.34	0.05	0.02	0.00	0.10	0.10	0.03	0.01	0.00	0.02	0.00
		product37	SAMSUNG	GALAXYAL	0.32	0.60	0.00	0.43	0.06	0.02	0.00	0.08	0.09	0.04	0.01	0.00	0.02	0.00
		product38	SAMSUNG	GALAXYS6	0.31	0.50	0.00	0.40	0.06	0.02	0.00	0.10	0.12	0.05	0.01	0.00	0.03	0.00
		product40	SAMSUNG	GALAXYS6	0.30	0.48	0.00	0.37	0.05	0.02	0.00	0.10	0.11	0.04	0.01	0.00	0.03	0.00
		product42	SAMSUNG	GALAXYS4	0.22	0.29	0.00	0.15	0.03	0.01	0.00	0.05	0.04	0.02	0.01	0.00	0.01	0.00
		product44	SAMSUNG	GALAXYN(	0.32	0.50	0.00	0.34	0.05	0.02	0.00	0.10	0.10	0.03	0.01	0.00	0.02	0.00
		product49	SAMSUNG	GALAXYA7	0.27	0.43	0.00	0.24	0.04	0.02	0.00	0.07	0.06	0.02	0.01	0.00	0.01	0.00
		product52	SONY	XPERIAZ3I	0.30	0.49	0.00	0.29	0.05	0.02	0.00	0.08	0.08	0.03	0.01	0.00	0.02	0.00
		product54	SONY	XPERIAZ2I	0.29	0.41	0.00	0.23	0.04	0.02	0.00	0.07	0.06	0.02	0.01	0.00	0.01	0.00
		product62	HTC	ONE32GBI	0.26	0.39	0.00	0.26	0.05	0.02	0.00	0.08	0.07	0.03	0.01	0.00	0.02	0.00
		product63	HTC	ONEM816	0.31	0.46	0.00	0.27	0.05	0.02	0.00	0.08	0.07	0.03	0.01	0.00	0.01	0.00
		product67	HTC	ONEM932	0.33	0.57	0.00	0.39	0.06	0.02	0.00	0.10	0.10	0.04	0.01	0.00	0.02	0.00
		product70	HTC	ONEM8S1	0.26	0.42	0.00	0.24	0.04	0.02	0.00	0.07	0.06	0.02	0.01	0.00	0.01	0.00
		product72	NOKIA	LUMIA930	0.28	0.44	0.00	0.30	0.05	0.02	0.00	0.08	0.08	0.03	0.01	0.00	0.02	0.00
		product74	NOKIA	LUMIA102	0.31	0.51	0.00	0.35	0.06	0.02	0.00	0.08	0.07	0.03	0.01	0.00	0.02	0.00
		product78	LG	D855G316	0.24	0.37	0.00	0.22	0.04	0.02	0.00	0.07	0.06	0.02	0.01	0.00	0.01	0.00
		product80	LG	H815G432	0.29	0.45	0.00	0.30	0.05	0.02	0.00	0.09	0.09	0.03	0.01	0.00	0.02	0.00
		product83	LG	D855G332	0.27	0.42	0.00	0.27	0.05	0.02	0.00	0.09	0.08	0.03	0.01	0.00	0.02	0.00
		product98	HUAWEI	ASCENDM	0.28	0.44	0.00	0.26	0.04	0.02	0.00	0.07	0.07	0.03	0.01	0.00	0.01	0.00

Table 22 Cross product-price elasticities of some products, France

		cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI			
		Min	(19.67)		Min	(19.67)	Min	(14.93)	Min	(6.70)	Min	(8.92)	Min	(1.30)	Min	(4.59)	Min	(1.83)		
		Max	1.59		Max	1.59	Max	(0.07)	Max	(3.72)	Max	0.65	Max	(1.07)	Max	(1.79)	Max	(1.83)		
		Avg	(7.68)		Avg	(8.91)	Avg	(7.91)	Avg	(5.21)	Avg	(3.93)	Avg	(1.18)	Avg	(2.80)	Avg	(1.83)		
all	France	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20	21	24
Min	(19.67)	product01	APPLE	IPHONE5S	(7.78)	0.22	0.00	0.11	0.02	0.02	0.00	0.04	0.03	0.02	0.00	0.00	0.01	(0.00)	0.00	0.06
Max	1.59	product02	APPLE	IPHONE61	0.10	(10.48)	0.00	0.13	0.03	0.02	0.00	0.05	0.04	0.03	0.00	0.00	0.02	(0.00)	0.00	0.06
Avg	(0.16)	product04	APPLE	IPHONE51	0.06	0.14	(3.51)	0.04	0.01	0.02	0.00	0.02	0.01	0.01	0.00	0.00	0.01	(0.00)	0.00	0.04
		product05	APPLE	IPHONE66	0.08	0.20	0.00	(11.73)	0.06	0.02	0.00	0.05	0.07	0.05	0.01	0.00	0.03	(0.00)	0.01	0.05
		product08	APPLE	IPHONE5S	0.08	0.21	0.00	0.26	(9.32)	0.02	0.00	0.05	0.06	0.05	0.01	0.00	0.03	(0.00)	0.01	0.05
		product10	APPLE	IPHONE5C	0.08	0.18	0.00	0.07	0.02	(3.16)	0.00	0.03	0.02	0.01	0.00	0.00	0.01	(0.00)	0.00	0.05
		product11	APPLE	IPHONE53	0.07	0.15	0.00	0.14	0.03	0.02	(4.89)	0.03	0.04	0.03	0.00	0.00	0.02	(0.00)	0.00	0.05
		product12	APPLE	IPHONE6P	0.09	0.20	0.00	0.14	0.03	0.02	0.00	(12.78)	0.04	0.03	0.01	0.00	0.02	(0.00)	0.00	0.06
		product14	APPLE	IPHONE6P	0.08	0.17	0.00	0.23	0.04	0.02	0.00	0.05	(16.72)	0.05	0.01	0.00	0.03	(0.00)	0.00	0.05
		product16	APPLE	IPHONE61	0.08	0.20	0.00	0.32	0.06	0.02	0.00	0.04	0.08	(16.70)	0.01	0.00	0.05	(0.00)	0.01	0.05
		product17	APPLE	IPHONE5S	0.08	0.21	0.00	0.29	0.06	0.02	0.00	0.05	0.07	0.05	(12.82)	0.00	0.03	(0.00)	0.01	0.05
		product18	APPLE	IPHONE56	0.07	0.17	0.00	0.24	0.05	0.02	0.00	0.04	0.06	0.05	0.01	(5.98)	0.03	(0.00)	0.00	0.05
		product19	APPLE	IPHONE6P	0.08	0.18	0.00	0.27	0.05	0.02	0.00	0.04	0.08	0.06	0.01	0.00	(19.67)	(0.00)	0.00	0.05
		product20	APPLE	IPHONE4S	0.06	0.13	0.00	0.20	0.04	0.02	0.00	0.03	0.05	0.04	0.01	0.00	0.03	1.59	0.00	0.04
		product21	APPLE	IPHONE5C	0.08	0.18	0.00	0.22	0.04	0.02	0.00	0.04	0.05	0.04	0.01	0.00	0.02	(0.00)	(4.87)	0.05
		product24	SAMSUNG	GALAXYS5	0.09	0.19	0.00	0.09	0.02	0.02	0.00	0.04	0.03	0.02	0.00	0.00	0.01	(0.00)	0.00	(3.72)
		product25	SAMSUNG	GALAXYS6	0.08	0.16	0.00	0.13	0.02	0.02	0.00	0.04	0.05	0.03	0.00	0.00	0.02	(0.00)	0.00	0.05
		product27	SAMSUNG	GALAXYS6	0.08	0.16	0.00	0.14	0.03	0.02	0.00	0.05	0.05	0.03	0.01	0.00	0.02	(0.00)	0.00	0.05
		product28	SAMSUNG	GALAXYN	0.09	0.18	0.00	0.10	0.02	0.02	0.00	0.04	0.03	0.02	0.00	0.00	0.02	(0.00)	0.00	0.05
		product30	SAMSUNG	GALAXYN	0.07	0.15	0.00	0.13	0.02	0.02	0.00	0.04	0.05	0.02	0.00	0.00	0.02	(0.00)	0.00	0.05
		product36	SAMSUNG	GALAXYS6	0.08	0.15	0.00	0.14	0.03	0.02	0.00	0.05	0.05	0.03	0.01	0.00	0.02	(0.00)	0.00	0.05
		product37	SAMSUNG	GALAXYAL	0.07	0.17	0.00	0.12	0.03	0.02	0.00	0.04	0.03	0.02	0.00	0.00	0.02	(0.00)	0.00	0.05
		product38	SAMSUNG	GALAXYS6	0.08	0.15	0.00	0.16	0.03	0.02	0.00	0.04	0.06	0.04	0.01	0.00	0.03	(0.00)	0.00	0.05
		product40	SAMSUNG	GALAXYS6	0.07	0.15	0.00	0.15	0.03	0.02	0.00	0.04	0.06	0.03	0.01	0.00	0.03	(0.00)	0.00	0.05
		product42	SAMSUNG	GALAXYS4	0.06	0.14	0.00	0.09	0.02	0.02	0.00	0.03	0.03	0.02	0.00	0.00	0.01	(0.00)	0.00	0.04
		product44	SAMSUNG	GALAXYN	0.08	0.15	0.00	0.14	0.03	0.02	0.00	0.05	0.05	0.03	0.01	0.00	0.02	(0.00)	0.00	0.05
		product49	SAMSUNG	GALAXYA7	0.08	0.18	0.00	0.11	0.02	0.02	0.00	0.04	0.04	0.02	0.00	0.00	0.01	(0.00)	0.00	0.05
		product52	SONY	XPERIAZ3	0.09	0.19	0.00	0.08	0.02	0.02	0.00	0.04	0.02	0.02	0.00	0.00	0.01	0.00	0.00	0.06
		product54	SONY	XPERIAZ2	0.06	0.14	0.00	0.05	0.01	0.02	0.00	0.03	0.01	0.01	0.00	0.00	0.01	(0.00)	0.00	0.04
		product62	HTC	ONE32GB	0.07	0.13	0.00	0.11	0.02	0.02	0.00	0.04	0.04	0.02	0.00	0.00	0.02	(0.00)	0.00	0.05
		product63	HTC	ONEM816	0.09	0.20	0.00	0.10	0.02	0.02	0.00	0.04	0.03	0.02	0.00	0.00	0.01	(0.00)	0.00	0.06
		product67	HTC	ONEM932	0.08	0.17	0.00	0.17	0.03	0.02	0.00	0.05	0.06	0.03	0.01	0.00	0.02	(0.00)	0.00	0.05
		product70	HTC	ONEM8S1	0.07	0.14	0.00	0.09	0.02	0.02	0.00	0.03	0.03	0.02	0.00	0.00	0.01	(0.00)	0.00	0.04
		product72	NOKIA	LUMIA930	0.06	0.12	0.00	0.11	0.02	0.02	0.00	0.04	0.04	0.02	0.00	0.00	0.02	(0.00)	0.00	0.04
		product74	NOKIA	LUMIA102	0.07	0.15	0.00	0.14	0.03	0.02	0.00	0.03	0.04	0.03	0.00	0.00	0.02	(0.00)	0.00	0.05
		product78	LG	D855G316	0.07	0.15	0.00	0.07	0.02	0.02	0.00	0.03	0.02	0.02	0.00	0.00	0.01	(0.00)	0.00	0.05
		product80	LG	H815G432	0.07	0.14	0.00	0.12	0.02	0.02	0.00	0.04	0.05	0.02	0.00	0.00	0.02	(0.00)	0.00	0.05
		product83	LG	D855G332	0.07	0.14	0.00	0.11	0.02	0.02	0.00	0.04	0.04	0.02	0.00	0.00	0.02	(0.00)	0.00	0.05
		product98	HUAWEI	ASCENDM	0.08	0.20	0.00	0.10	0.02	0.02	0.00	0.04	0.03	0.02	0.00	0.00	0.01	(0.00)	0.00	0.05

Table 23 Cross product-price elasticities of some products, Germany

		cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI			
		Min	(17.50)		Min	(17.50)	Min	(14.79)	Min	(3.61)	Min	(7.68)	Min	0.39	Min	(4.22)	Min	0.74		
		Max	2.94		Max	(1.24)	Max	2.94	Max	(0.24)	Max	1.89	Max	2.71	Max	1.13	Max	0.74		
		Avg	(6.18)		Avg	(8.10)	Avg	(5.94)	Avg	(1.92)	Avg	(1.94)	Avg	1.55	Avg	(1.15)	Avg	0.74		
All	Germany	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20	21	24
Min	(17.50)	product01	APPLE	IPHONE5S	(6.44)	0.41	0.00	0.22	0.07	0.03	0.00	0.06	0.04	0.04	0.02	0.00	0.02	0.00	0.01	0.18
Max	2.94	product02	APPLE	IPHONE61	0.28	(8.64)	0.00	0.35	0.08	0.01	0.00	0.07	0.06	0.07	0.02	0.00	0.03	0.00	0.01	0.13
Avg	(0.08)	product04	APPLE	IPHONE51	0.28	0.40	(1.24)	0.28	0.07	0.01	0.00	0.05	0.05	0.05	0.02	0.00	0.02	0.00	0.01	0.14
		product05	APPLE	IPHONE66	0.23	0.32	0.00	(10.74)	0.08	0.01	0.00	0.04	0.12	0.14	0.03	0.00	0.06	0.00	0.01	0.12
		product08	APPLE	IPHONE5S	0.28	0.48	0.00	0.40	(8.85)	0.01	0.00	0.07	0.07	0.07	0.03	0.00	0.03	0.00	0.01	0.13
		product10	APPLE	IPHONE5C	0.31	0.38	0.00	0.28	0.05	(1.96)	0.00	0.05	0.04	0.04	0.01	0.00	0.02	0.00	0.01	0.29
		product11	APPLE	IPHONE53	0.24	0.37	0.00	0.59	0.08	0.01	(3.47)	0.05	0.09	0.10	0.03	0.00	0.04	0.00	0.01	0.12
		product12	APPLE	IPHONE6P	0.29	0.51	0.00	0.36	0.08	0.01	0.00	(12.63)	0.06	0.07	0.03	0.00	0.03	0.00	0.01	0.13
		product14	APPLE	IPHONE6P	0.23	0.32	0.00	0.76	0.07	0.01	0.00	0.04	(15.01)	0.14	0.03	0.00	0.06	0.00	0.01	0.12
		product16	APPLE	IPHONE61	0.22	0.31	0.00	0.90	0.08	0.01	0.00	0.04	0.13	(14.71)	0.03	0.00	0.08	0.00	0.01	0.11
		product17	APPLE	IPHONE5S	0.23	0.32	0.00	0.85	0.08	0.01	0.00	0.04	0.12	0.14	(11.57)	0.00	0.06	0.00	0.01	0.12
		product18	APPLE	IPHONE56	0.23	0.32	0.00	0.80	0.07	0.01	0.00	0.04	0.11	0.14	0.03	(6.10)	0.06	0.00	0.01	0.11
		product19	APPLE	IPHONE6P	0.22	0.31	0.00	0.79	0.08	0.01	0.00	0.04	0.13	0.18	0.03	0.00	(17.50)	0.00	0.01	0.11
		product20	APPLE	IPHONE4S	0.23	0.31	0.00	0.84	0.07	0.01	0.00	0.04	0.12	0.14	0.03	0.00	0.06	(4.75)	0.01	0.12
		product21	APPLE	IPHONE5C	0.18	0.30	0.00	0.70	0.06	0.02	0.00	0.04	0.10	0.11	0.02	0.00	0.05	0.00	(4.05)	0.12
		product24	SAMSUNG	GALAXYS5	0.28	0.41	0.00	0.23	0.06	0.04	0.00	0.06	0.04	0.04	0.02	0.00	0.02	0.00	0.01	(1.87)
		product25	SAMSUNG	GALAXYS6	0.25	0.41	0.00	0.41	0.08	0.01	0.00	0.06	0.07	0.08	0.03	0.00	0.04	0.00	0.01	0.12
		product27	SAMSUNG	GALAXYS6	0.29	0.45	0.00	0.37	0.08	0.01	0.00	0.06	0.06	0.07	0.03	0.00	0.03	0.00	0.01	0.14
		product28	SAMSUNG	GALAXYN	0.23	0.32	0.00	0.50	0.07	0.01	0.00	0.04	0.09	0.10	0.03	0.00	0.04	0.00	0.01	0.12
		product30	SAMSUNG	GALAXYN	0.27	0.45	0.00	0.39	0.08	0.01	0.00	0.06	0.07	0.08	0.03	0.00	0.03	0.00	0.01	0.13
		product36	SAMSUNG	GALAXYS6	0.24	0.36	0.00	0.48	0.07	0.01	0.00	0.05	0.09	0.09	0.03	0.00	0.04	0.00	0.01	0.12
		product37	SAMSUNG	GALAXYAL	0.23	0.29	0.00	0.53	0.06	0.01	0.00	0.04	0.08	0.08	0.02	0.00	0.04	0.00	0.01	0.14
		product38	SAMSUNG	GALAXYS6	0.27	0.42	0.00	0.45	0.08	0.01	0.00	0.06	0.08	0.10	0.03	0.00	0.04	0.00	0.01	0.13
		product40	SAMSUNG	GALAXYS6	0.24	0.33	0.00	0.53	0.07	0.01	0.00	0.04	0.09	0.11	0.03	0.00	0.05	0.00	0.01	0.12
		product42	SAMSUNG	GALAXYS4	0.28	0.32	0.00	0.23	0.06	0.01	0.00	0.04	0.04	0.04	0.02	0.00	0.02	0.00	0.01	0.15
		product44	SAMSUNG	GALAXYN	0.28	0.48	0.00	0.39	0.08	0.01	0.00	0.07	0.07	0.08	0.03	0.00	0.03	0.00	0.01	0.13
		product49	SAMSUNG	GALAXYA7	0.23	0.35	0.00	0.46	0.07	0.01	0.00	0.05	0.08	0.08	0.02	0.00	0.04	0.00	0.01	0.11
		product52	SONY	XPERIAZ3	0.38	0.33	0.00	0.13	0.05	0.03	0.00	0.04	0.02	0.02	0.01	0.00	0.01	0.00	0.01	0.24
		product54	SONY	XPERIAZ2	0.32	0.35	0.00	0.17	0.05	0.05	0.00	0.05	0.03	0.03	0.01	0.00	0.02	0.00	0.01	0.30
		product62	HTC	ONE32GB	0.21	0.29	0.00	0.43	0.06	0.01	0.00	0.04	0.08	0.08	0.02	0.00	0.04	0.00	0.01	0.11
		product63	HTC	ONEM816	0.32	0.37	0.00	0.21	0.06	0.04	0.00	0.05	0.04	0.04	0.02	0.00	0.02	0.00	0.01	0.28
		product67	HTC	ONEM932	0.30	0.45	0.00	0.29	0.07	0.02	0.00	0.06	0.05	0.06	0.02	0.00	0.03	0.00	0.01	0.17
		product70	HTC	ONEM8S1	0.26	0.30	0.00	0.09	0.03	0.03	0.00	0.04	0.02	0.02	0.01	0.00	0.01	0.00	0.01	0.21
		product72	NOKIA	LUMIA930	0.25	0.30	0.00	0.27	0.05	0.03	0.00	0.04	0.05	0.06	0.02	0.00	0.03	0.00	0.01	0.22
		product74	NOKIA	LUMIA102	0.21	0.25	0.00	0.47	0.06	0.01	0.00	0.03	0.08	0.08	0.02	0.00	0.04	0.00	0.01	0.12
		product78	LG	D855G316	0.28	0.35	0.00	0.25	0.06	0.02	0.00	0.05	0.05	0.05	0.02	0.00	0.02	0.00	0.01	0.14
		product80	LG	H815G432	0.24	0.36	0.00	0.44	0.07	0.01	0.00	0.05	0.08	0.09	0.03	0.00	0.04	0.00	0.01	0.12
		product83	LG	D855G332	0.22	0.31	0.00	0.43	0.07	0.01	0.00	0.04	0.08	0.09	0.03	0.00	0.04	0.00	0.01	0.11
		product98	HUAWEI	ASCENDM	0.23	0.36	0.00	0.43	0.07	0.01	0.00	0.05	0.08	0.08	0.02	0.00	0.04	0.00	0.01	0.12

Table 24 Cross product-price elasticities of some products, Spain

		cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI			
		Min	(19.52)		Min	(19.52)	Min	(14.08)	Min	(5.94)	Min	(10.76)	Min	(0.20)	Min	(6.08)	Min	(1.27)		
		Max	2.25		Max	(2.70)	Max	1.11	Max	(3.24)	Max	2.25	Max	(0.04)	Max	(0.39)	Max	(1.27)		
		Avg	(7.37)		Avg	(9.16)	Avg	(6.95)	Avg	(4.59)	Avg	(3.73)	Avg	(0.12)	Avg	(2.67)	Avg	(1.27)		
All	Spain	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20	21	24
Min	(19.52)	product01	APPLE	IPHONE5S	(7.12)	0.23	0.00	0.07	0.01	0.01	0.00	0.07	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.09
Max	2.25	product02	APPLE	IPHONE61	0.10	(9.67)	0.00	0.08	0.01	0.01	0.00	0.07	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.08
Avg	(0.15)	product04	APPLE	IPHONE51	0.10	0.19	(2.70)	0.03	0.01	0.01	0.00	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.10
		product05	APPLE	IPHONE66	0.07	0.14	0.00	(11.53)	0.02	0.01	0.00	0.04	0.06	0.03	0.00	0.00	0.02	0.00	0.00	0.06
		product08	APPLE	IPHONE5S	0.08	0.14	0.00	0.24	(8.59)	0.01	0.00	0.04	0.05	0.02	0.00	0.00	0.02	0.00	0.00	0.06
		product10	APPLE	IPHONE5C	0.10	0.20	0.00	0.06	0.01	(3.20)	0.00	0.05	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.08
		product11	APPLE	IPHONE53	0.10	0.16	0.01	0.12	0.01	0.01	(4.73)	0.05	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.08
		product12	APPLE	IPHONE6P	0.10	0.25	0.00	0.08	0.01	0.01	0.00	(14.04)	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.08
		product14	APPLE	IPHONE6P	0.07	0.14	0.00	0.20	0.01	0.01	0.00	0.04	(15.65)	0.03	0.00	0.00	0.02	0.00	0.00	0.06
		product16	APPLE	IPHONE61	0.03	0.10	0.00	0.30	0.01	0.00	0.00	0.03	0.07	(15.64)	0.02	0.00	0.05	0.00	0.00	0.03
		product17	APPLE	IPHONE5S	0.04	0.11	0.00	0.29	0.01	0.00	0.00	0.03	0.06	0.05	(11.04)	0.00	0.04	0.00	0.00	0.04
		product18	APPLE	IPHONE56	0.08	0.13	0.00	0.27	0.02	0.01	0.00	0.04	0.05	0.03	0.00	(8.72)	0.02	0.00	0.00	0.06
		product19	APPLE	IPHONE6P	0.04	0.12	0.00	0.25	0.01	0.00	0.00	0.03	0.07	0.05	0.01	0.00	(19.52)	0.00	0.00	0.04
		product20	APPLE	IPHONE4S	0.09	0.14	0.00	0.25	0.02	0.01	0.00	0.04	0.05	0.03	0.00	0.00	0.02	(6.30)	0.00	0.07
		product21	APPLE	IPHONE5C	0.06	0.12	0.00	0.22	0.01	0.01	0.00	0.04	0.05	0.03	0.01	0.00	0.02	0.00	(4.62)	0.05
		product24	SAMSUNG	GALAXYS5	0.11	0.21	0.00	0.05	0.01	0.01	0.00	0.06	0.02	0.00	0.00	0.00	0.00	0.00	0.00	(3.55)
		product25	SAMSUNG	GALAXYS6	0.10	0.22	0.00	0.08	0.01	0.01	0.00	0.06	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.08
		product27	SAMSUNG	GALAXYS6	0.10	0.23	0.00	0.08	0.01	0.01	0.00	0.07	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.08
		product28	SAMSUNG	GALAXYN(	0.10	0.21	0.00	0.07	0.01	0.01	0.00	0.06	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.08
		product30	SAMSUNG	GALAXYN(	0.09	0.22	0.00	0.08	0.01	0.01	0.00	0.07	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.07
		product36	SAMSUNG	GALAXYS6	0.10	0.21	0.00	0.09	0.01	0.01	0.00	0.06	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.07
		product37	SAMSUNG	GALAXYAL	0.07	0.15	0.00	0.15	0.01	0.01	0.00	0.04	0.04	0.02	0.00	0.00	0.01	0.00	0.00	0.06
		product38	SAMSUNG	GALAXYS6	0.08	0.14	0.00	0.12	0.01	0.01	0.00	0.04	0.05	0.01	0.00	0.00	0.02	0.00	0.00	0.06
		product40	SAMSUNG	GALAXYS6	0.08	0.14	0.00	0.12	0.01	0.01	0.00	0.04	0.05	0.01	0.00	0.00	0.02	0.00	0.00	0.06
		product42	SAMSUNG	GALAXYS4	0.07	0.17	0.00	0.06	0.01	0.01	0.00	0.05	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.06
		product44	SAMSUNG	GALAXYN(	0.10	0.22	0.00	0.08	0.01	0.01	0.00	0.06	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.08
		product49	SAMSUNG	GALAXYA7	0.08	0.19	0.00	0.06	0.01	0.01	0.00	0.05	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.07
		product52	SONY	XPERIAZ3I	0.10	0.23	0.00	0.05	0.01	0.01	0.00	0.06	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.09
		product54	SONY	XPERIAZ2I	0.08	0.17	0.01	0.03	0.00	0.01	0.00	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.11
		product62	HTC	ONE32GBI	0.08	0.14	0.00	0.03	0.01	0.01	0.00	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.08
		product63	HTC	ONEM816	0.09	0.21	0.00	0.05	0.01	0.01	0.00	0.06	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.10
		product67	HTC	ONEM932	0.10	0.24	0.00	0.08	0.01	0.01	0.00	0.07	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.08
		product70	HTC	ONEM8S1	0.08	0.18	0.00	0.04	0.01	0.01	0.00	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.08
		product72	NOKIA	LUMIA930	0.06	0.11	0.00	0.10	0.01	0.01	0.00	0.03	0.04	0.02	0.00	0.00	0.02	0.00	0.00	0.05
		product74	NOKIA	LUMIA102	0.08	0.12	0.00	0.13	0.01	0.01	0.00	0.03	0.04	0.01	0.00	0.00	0.01	0.00	0.00	0.06
		product78	LG	D855G316	0.09	0.19	0.00	0.06	0.01	0.01	0.00	0.05	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.09
		product80	LG	H815G432	0.09	0.20	0.00	0.08	0.01	0.01	0.00	0.06	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.07
		product83	LG	D855G332	0.07	0.12	0.00	0.09	0.01	0.01	0.00	0.03	0.04	0.01	0.00	0.00	0.01	0.00	0.00	0.05
		product98	HUAWEI	ASCENDM	0.07	0.17	0.00	0.09	0.01	0.01	0.00	0.05	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.06

Table 25 Cross product-price elasticities of some products, Austria

cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI	
Min	(17.18)		Min	(17.18)	Min	(12.87)	Min	(3.64)	Min	(6.39)	Min	0.20	Min	(1.99)	Min	0.74
Max	0.40		Max	(1.45)	Max	0.27	Max	(0.29)	Max	0.40	Max	1.12	Max	0.83	Max	0.74
Avg	(6.05)		Avg	(7.78)	Avg	(5.88)	Avg	(1.96)	Avg	(2.23)	Avg	0.66	Avg	(0.45)	Avg	0.74

All	Austria	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20	21	24	25	27	28	30	36	37	38	40	42	44	49	52	54	62	63	67	70	72	74	78	80	83	98
Min	(17.18)	product01	APPLE	IPHONE5S	(6.13)	0.47	0.00	0.14	0.02	0.02	0.00	0.06	0.03	0.03	0.03	0.00	0.01	0.00	(0.00)	0.10	0.09	0.07	0.02	0.06	0.03	0.00	0.02	0.04	0.00	0.01	(0.00)	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
Max	1.12	product02	APPLE	IPHONE61	0.18	(9.01)	0.00	0.17	0.03	0.01	0.00	0.06	0.03	0.03	0.04	0.00	0.01	0.00	0.00	0.12	0.10	0.08	0.03	0.06	0.04	0.00	0.02	0.04	0.00	0.01	(0.00)	0.02	0.01	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
Avg	(0.09)	product04	APPLE	IPHONE51	0.16	0.39	(1.45)	0.14	0.02	0.02	0.00	0.05	0.02	0.03	0.03	0.00	0.01	0.00	0.00	0.09	0.08	0.06	0.02	0.05	0.03	(0.00)	0.02	0.04	0.00	0.01	(0.00)	0.02	0.00	0.00	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.00	(0.00)
		product05	APPLE	IPHONE66	0.15	0.33	0.00	(10.68)	0.04	0.01	0.00	0.05	0.07	0.09	0.04	0.00	0.03	0.00	(0.00)	0.12	0.13	0.11	0.03	0.05	0.06	0.00	0.04	0.06	0.00	0.01	(0.00)	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product08	APPLE	IPHONE5S	0.15	0.34	0.00	0.38	(8.34)	0.01	0.00	0.05	0.06	0.07	0.04	0.00	0.02	0.00	(0.00)	0.12	0.13	0.11	0.03	0.05	0.05	0.00	0.04	0.06	0.00	0.01	(0.00)	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product10	APPLE	IPHONE5C	0.17	0.39	0.00	0.09	0.02	(1.67)	0.00	0.05	0.02	0.02	0.03	0.00	0.01	0.00	(0.00)	0.09	0.06	0.05	0.02	0.05	0.02	0.00	0.01	0.03	0.00	0.00	(0.00)	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product11	APPLE	IPHONE53	0.15	0.34	0.00	0.27	0.03	0.01	(4.13)	0.05	0.04	0.05	0.03	0.00	0.02	0.00	(0.00)	0.11	0.11	0.08	0.02	0.05	0.04	0.00	0.03	0.05	0.00	0.01	(0.00)	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product12	APPLE	IPHONE6P	0.17	0.48	0.00	0.17	0.03	0.01	0.00	(12.07)	0.03	0.03	0.04	0.00	0.01	0.00	0.00	0.12	0.12	0.09	0.03	0.06	0.04	0.00	0.03	0.04	0.00	0.01	(0.00)	0.02	0.01	0.01	0.02	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product14	APPLE	IPHONE6P	0.15	0.31	0.00	0.35	0.04	0.01	0.00	0.05	(14.73)	0.08	0.04	0.00	0.03	0.00	0.00	0.12	0.17	0.14	0.03	0.06	0.07	0.00	0.05	0.08	0.00	0.01	(0.00)	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product16	APPLE	IPHONE61	0.14	0.28	0.00	0.48	0.04	0.01	0.00	0.04	0.08	(15.45)	0.05	0.00	0.05	0.00	(0.00)	0.11	0.13	0.11	0.03	0.05	0.06	0.00	0.05	0.07	0.00	0.01	(0.00)	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product17	APPLE	IPHONE5S	0.15	0.36	0.00	0.42	0.04	0.01	0.00	0.05	0.06	0.08	(11.13)	0.00	0.03	0.00	(0.00)	0.12	0.12	0.10	0.03	0.05	0.05	0.00	0.04	0.06	0.00	0.01	(0.00)	0.02	0.01	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product18	APPLE	IPHONE56	0.14	0.28	0.00	0.38	0.04	0.01	0.00	0.04	0.06	0.10	0.04	(4.60)	0.04	0.00	(0.00)	0.11	0.13	0.11	0.03	0.04	0.05	0.00	0.04	0.06	0.00	0.01	(0.00)	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product19	APPLE	IPHONE6P	0.14	0.27	0.00	0.42	0.04	0.01	0.00	0.04	0.08	0.12	0.05	0.00	(17.18)	0.00	0.00	0.11	0.15	0.13	0.03	0.05	0.06	(0.00)	0.06	0.08	0.00	0.01	(0.00)	0.01	0.01	0.01	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.00	(0.00)
		product20	APPLE	IPHONE4S	0.14	0.29	0.00	0.41	0.04	0.01	0.00	0.04	0.06	0.08	0.04	0.00	0.03	(2.88)	(0.00)	0.11	0.12	0.10	0.03	0.04	0.05	(0.00)	0.04	0.06	0.00	0.01	(0.00)	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product21	APPLE	IPHONE5C	0.14	0.27	0.00	0.31	0.04	0.01	0.00	0.04	0.05	0.07	0.04	0.00	0.03	0.00	(2.90)	0.12	0.13	0.11	0.03	0.04	0.05	(0.00)	0.03	0.06	0.00	0.01	(0.00)	0.01	0.01	0.01	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.00	0.00	(0.00)
		product24	SAMSUNG	GALAXYS5	0.16	0.39	0.00	0.16	0.03	0.01	0.00	0.05	0.03	0.03	0.04	0.00	0.01	0.00	0.00	(2.15)	0.15	0.11	0.03	0.06	0.06	0.00	0.03	0.06	0.00	0.01	(0.00)	0.02	0.01	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product25	SAMSUNG	GALAXYS6	0.15	0.30	0.00	0.20	0.03	0.01	0.00	0.05	0.04	0.04	0.04	0.00	0.02	0.00	0.00	0.11	(6.03)	0.20	0.03	0.07	0.09	0.00	0.05	0.10	0.00	0.02	(0.00)	0.02	0.01	0.01	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)
		product27	SAMSUNG	GALAXYS6	0.15	0.31	0.00	0.21	0.03	0.01	0.00	0.05	0.05	0.04	0.04	0.00	0.02	0.00	0.00	0.12	0.25	(10.08)	0.03	0.07	0.09	0.00	0.05	0.10	0.00	0.02	(0.00)	0.02	0.01	0.01	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)
		product28	SAMSUNG	GALAXYNC	0.14	0.29	0.00	0.21	0.03	0.01	0.00	0.04	0.05	0.04	0.04	0.00	0.02	0.00	(0.00)	0.11	0.23	0.17	(2.15)	0.06	0.08	(0.00)	0.05	0.09	0.00	0.01	(0.00)	0.01	0.01	0.01	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)
		product30	SAMSUNG	GALAXYNC	0.16	0.41	0.00	0.17	0.03	0.01	0.00	0.05	0.03	0.04	0.04	0.00	0.01	0.00	0.00	0.12	0.18	0.13	0.03	(6.44)	0.07	0.00	0.03	0.07	0.00	0.01	(0.00)	0.02	0.01	0.01	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)
		product36	SAMSUNG	GALAXYS6	0.15	0.31	0.00	0.21	0.03	0.01	0.00	0.05	0.05	0.04	0.04	0.00	0.02	0.00	0.00	0.12	0.25	0.19	0.03	0.07	(10.91)	0.00	0.05	0.09	0.00	0.02	(0.00)	0.02	0.01	0.01	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)
		product37	SAMSUNG	GALAXYAL	0.13	0.28	0.00	0.27	0.03	0.01	0.00	0.04	0.05	0.05	0.04	0.00	0.02	0.00	(0.00)	0.11	0.15	0.12	0.03	0.05	0.06	0.13	0.04	0.06	0.00	0.01	(0.00)	0.01	0.01	0.00	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.00	0.00	(0.00)
		product38	SAMSUNG	GALAXYS6	0.15	0.31	0.00	0.25	0.03	0.01	0.00	0.05	0.06	0.05	0.04	0.00	0.02	0.00	0.00	0.12	0.23	0.18	0.03	0.07	0.08	0.00	(12.87)	0.10	0.00	0.02	(0.00)	0.02	0.01	0.01	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)
		product40	SAMSUNG	GALAXYS6	0.15	0.28	0.00	0.21	0.03	0.02	0.00	0.04	0.05	0.05	0.04	0.00	0.02	0.00	0.00	0.10	0.23	0.18	0.03	0.06	0.08	(0.00)	0.06	(8.12)	0.00	0.02	(0.00)	0.02	0.01	0.00	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)
		product42	SAMSUNG	GALAXYS4	0.14	0.30	0.00	0.12	0.02	0.02	0.00	0.04	0.02	0.03	0.03	0.00	0.01	0.00	(0.00)	0.10	0.13	0.10	0.02	0.05	0.05	(0.00)	0.03	0.05	0.26	0.01	(0.00)	0.02	0.01	0.00	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.00	0.00	(0.00)
		product44	SAMSUNG	GALAXYNC	0.15	0.31	0.00	0.22	0.03	0.01	0.00	0.05	0.05	0.04	0.04	0.00	0.02	0.00	0.00	0.12	0.25	0.19	0.03	0.07	0.09	0.00	0.05	0.09	0.00	(12.51)	(0.00)	0.02	0.01	0.01	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)
		product49	SAMSUNG	GALAXYA7	0.14	0.29	0.00	0.18	0.03	0.01	0.00	0.04	0.04	0.04	0.03	0.00	0.02	0.00	(0.00)	0.11	0.21	0.16	0.03	0.06	0.08	(0.00)	0.04	0.07	0.00	0.01	0.27	0.02	0.01	0.00	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)
		product52	SONY	XPERIAZ3N	0.16	0.44	0.00	0.13	0.02	0.02	0.00	0.05	0.03	0.03	0.03	0.00	0.01	0.00	0.00	0.10	0.09	0.07	0.02	0.06	0.04	0.00	0.02	0.04	0.00	0.01	(0.00)	(3.64)	0.01	0.00	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product54	SONY	XPERIAZ2N	0.16	0.41	0.00	0.14	0.02	0.01	0.00	0.05	0.03	0.03	0.03	0.00	0.01	0.00	0.00	0.11	0.11	0.08	0.03	0.06	0.04	0.00	0.02	0.04	0.00	0.01	(0.00)	0.02	(0.29)	0.00	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product62	HTC	ONE32GBI	0.14	0.27	0.00	0.15	0.03	0.01	0.00	0.04	0.03	0.03	0.03	0.00	0.01	0.00	(0.00)	0.11	0.18	0.13	0.03	0.06	0.06	(0.00)	0.04	0.07	0.00	0.01	(0.00)	0.01	0.01	0.40	0.01	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.00	(0.00)
		product63	HTC	ONEM816	0.16	0.44	0.00	0.16	0.03	0.01	0.00	0.06	0.03	0.03	0.03	0.00	0.01	0.00	0.00	0.12	0.12	0.09	0.03	0.06	0.04	0.00	0.03	0.05	0.00	0.01	(0.00)	0.02	0.01	0.01	(2.30)	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product67	HTC	ONEM932	0.16	0.37	0.00	0.22	0.03	0.01	0.00	0.05	0.04	0.04	0.04	0.00	0.02	0.00	0.00	0.12	0.17	0.13	0.03	0.06	0.06	0.00	0.04	0.07	0.00	0.01	(0.00)	0.02	0.01	0.01	0.01	(6.39)	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product70	HTC	ONEM8S1	0.16	0.42	0.00	0.13	0.02	0.01	0.00	0.05	0.03	0.03	0.03	0.00	0.01	0.00	0.00	0.10	0.11	0.09	0.03	0.06	0.04	0.00	0.02	0.04	0.00	0.01	(0.00)	0.02	0.01	0.00	0.01	0.01	(0.62)	0.00	0.00	(0.00)	0.00	0.00	(0.00)
		product72	NOKIA	LUMIA930	0.13	0.26	0.00	0.19	0.03	0.01	0.00	0.04	0.04	0.04	0.04	0.00	0.02	0.00	0.00	0.11	0.22	0.17	0.03	0.06	0.08	(0.00)	0.04	0.08	0.00	0.01	(0.00)	0.01	0.01	0.00	0.01	0.01	(0.00)	0.20	0.00	(0.00)	0.01	0.00	(0.00)
		product74	NOKIA	LUMIA102	0.14	0.30	0.00	0.18	0.03	0.01	0.00	0.04	0.03	0.05	0.03	0.00	0.02	0.00	(0.00)	0.10	0.10	0.07	0.03	0.05	0.04	(0.00)	0.02	0.04	0.00	0.01	(0.00)	0.01	0.01	0.00	0.01	0.01	0.00	(0.00)	1.12	(0.00)	0.00	0.00	(0.00)
		product78	LG	D855G316	0.13	0.26	0.00	0.16	0.03	0.01	0.00	0.04	0.03	0.04	0.03	0.00	0.02	0.00	(0.00)	0.11	0.28	0.19	0.03	0.07	0.10	(0.00)	0.04	0.09	0.00	0.02	(0.00)	0.01	0.01	0.00	0.01	0.01	(0.00)	(0.00)	0.00	0.83	0.01	(0.00)	(0.00)
		product80	LG	H815G432	0.14	0.30	0.00	0.18	0.03	0.01	0.00	0.05	0.04	0.04	0.04	0.00	0.02	0.00	0.00	0.11	0.26	0.19	0.03	0.07	0.09	0.00	0.05	0.09	0.00	0.02	(0.00)	0.02	0.01	0.00	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	(1.99)	0.00	(0.00)
		product83	LG	D855G332	0.13	0.25	0.00	0.17	0.03	0.01	0.00	0.04	0.04	0.05	0.04	0.00	0.02	0.00	(0.00)	0.11	0.29	0.20	0.03	0.07	0.10	(0.00)	0.05	0.10	0.00	0.02	(0.00)	0.01	0.01	0.00	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	(0.19)	(0.00)
		product98	HUAWEI	ASCENDM	0.14	0.31	0.00	0.17	0.03	0.01	0.00	0.04	0.04	0.04	0.03	0.00	0.01	0.00	(0.00)	0.10	0.21	0.15	0.03	0.06	0.07	(0.00)	0.04	0.07	0.00	0.01	(0.00)	0.02	0.01	0.00	0.01	0.01	(0.00)	(0.00)	0.00	(0.00)	0.01	0.00	0.74

Table 26 Cross product-price elasticities of some products, Belgium

		cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI																										
		Min	(18.56)		Min	(18.56)	Min	(13.34)	Min	(4.71)	Min	(9.39)	Min	0.25	Min	(2.93)	Min	(0.75)																									
		Max	1.25		Max	(0.98)	Max	0.32	Max	(1.38)	Max	1.25	Max	2.35	Max	(0.90)	Max	(0.75)																									
		Avg	(6.89)		Avg	(8.54)	Avg	(6.91)	Avg	(3.04)	Avg	(3.41)	Avg	1.30	Avg	(2.04)	Avg	(0.75)																									
All	Belgium	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20	21	24	25	27	28	30	36	37	38	40	42	44	49	52	54	62	63	67	70	72	74	78	80	83	98
Min	(18.56)	product01	APPLE	IPHONE5S	(5.87)	0.35	0.00	0.32	0.06	0.02	0.00	0.04	0.05	0.05	0.01	0.00	0.02	0.00	0.00	0.11	0.15	0.09	0.01	0.02	0.03	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
Max	2.35	product02	APPLE	IPHONE61	0.24	(8.40)	0.00	0.33	0.06	0.02	0.00	0.04	0.06	0.05	0.01	0.00	0.02	0.00	0.00	0.12	0.16	0.10	0.01	0.02	0.03	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
Avg	(0.11)	product04	APPLE	IPHONE51	0.24	0.37	(6.48)	0.35	0.07	0.02	0.00	0.04	0.05	0.05	0.02	0.00	0.02	0.00	0.00	0.11	0.15	0.09	0.01	0.02	0.03	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product05	APPLE	IPHONE66	0.23	0.35	0.00	(11.14)	0.07	0.02	0.00	0.04	0.09	0.14	0.02	0.00	0.06	0.00	0.00	0.11	0.17	0.10	0.01	0.02	0.03	0.01	0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product08	APPLE	IPHONE5S	0.24	0.37	0.00	0.44	(8.87)	0.02	0.00	0.04	0.07	0.08	0.02	0.00	0.03	0.00	0.00	0.11	0.16	0.10	0.01	0.02	0.03	0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product10	APPLE	IPHONE5C	0.22	0.29	0.00	0.28	0.06	(2.17)	0.00	0.03	0.05	0.05	0.01	0.00	0.02	0.00	0.00	0.11	0.15	0.08	0.01	0.02	0.03	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product11	APPLE	IPHONE53	0.24	0.37	0.00	0.44	0.07	0.02	(7.51)	0.04	0.07	0.08	0.02	0.00	0.03	0.00	0.00	0.11	0.16	0.10	0.01	0.02	0.03	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product12	APPLE	IPHONE6P	0.23	0.34	0.00	0.28	0.06	0.02	0.00	(11.97)	0.05	0.04	0.01	0.00	0.02	0.00	0.00	0.12	0.18	0.11	0.01	0.02	0.04	0.00	0.02	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product14	APPLE	IPHONE6P	0.23	0.34	0.00	0.55	0.07	0.02	0.00	0.04	(14.61)	0.11	0.02	0.00	0.05	0.00	0.00	0.11	0.20	0.12	0.01	0.02	0.04	0.01	0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product16	APPLE	IPHONE61	0.23	0.32	0.00	0.90	0.08	0.02	0.00	0.03	0.12	(15.19)	0.03	0.00	0.10	(0.00)	0.01	0.10	0.17	0.10	0.01	0.02	0.03	0.01	0.04	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	(0.00)	0.00	0.00	0.00	0.00
		product17	APPLE	IPHONE5S	0.23	0.34	0.00	0.70	0.07	0.02	0.00	0.04	0.10	0.16	(10.49)	0.00	0.07	0.00	0.00	0.11	0.17	0.10	0.01	0.02	0.03	0.01	0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product18	APPLE	IPHONE56	0.23	0.32	0.00	0.67	0.07	0.02	0.00	0.03	0.10	0.16	0.03	(5.70)	0.07	0.00	0.00	0.11	0.18	0.10	0.01	0.02	0.03	0.01	0.04	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product19	APPLE	IPHONE6P	0.22	0.31	0.00	0.85	0.08	0.02	0.00	0.03	0.12	0.23	0.03	0.00	(18.56)	0.00	0.01	0.10	0.19	0.11	0.01	0.02	0.04	0.01	0.04	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product20	APPLE	IPHONE4S	0.22	0.29	0.00	0.67	0.07	0.02	0.00	0.03	0.09	0.16	0.03	0.00	0.07	(0.98)	0.00	0.10	0.17	0.10	0.01	0.02	0.03	0.01	0.03	0.03	0.00	0.00	0.00	0.00	0.00	(0.00)	0.00	0.01	0.00	(0.00)	(0.00)	0.00	0.00	0.00	0.00
		product21	APPLE	IPHONE5C	0.23	0.34	0.00	0.41	0.07	0.02	0.00	0.04	0.06	0.08	0.02	0.00	0.03	0.00	(4.06)	0.11	0.17	0.10	0.01	0.02	0.03	0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product24	SAMSUNG	GALAXYS5	0.20	0.24	0.00	0.20	0.05	0.02	0.00	0.03	0.04	0.03	0.01	0.00	0.01	0.00	0.00	(4.61)	0.14	0.08	0.01	0.02	0.03	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product25	SAMSUNG	GALAXYS6	0.21	0.28	0.00	0.29	0.06	0.02	0.00	0.04	0.05	0.05	0.01	0.00	0.02	0.00	0.00	0.12	(5.89)	0.15	0.01	0.03	0.05	0.00	0.03	0.03	0.00	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product27	SAMSUNG	GALAXYS6	0.22	0.30	0.00	0.29	0.06	0.02	0.00	0.04	0.06	0.04	0.01	0.00	0.02	0.00	0.00	0.12	0.25	(11.09)	0.01	0.03	0.05	0.00	0.03	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product28	SAMSUNG	GALAXYNC	0.21	0.29	0.00	0.31	0.06	0.02	0.00	0.04	0.05	0.05	0.01	0.00	0.02	0.00	0.00	0.12	0.23	0.13	(3.55)	0.03	0.04	0.00	0.03	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product30	SAMSUNG	GALAXYNC	0.21	0.29	0.00	0.28	0.06	0.02	0.00	0.04	0.05	0.04	0.01	0.00	0.02	0.00	0.00	0.12	0.27	0.15	0.01	(7.14)	0.05	0.00	0.03	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product36	SAMSUNG	GALAXYS6	0.22	0.31	0.00	0.28	0.06	0.02	0.00	0.04	0.06	0.04	0.01	0.00	0.02	0.00	0.00	0.12	0.25	0.14	0.01	0.03	(11.80)	0.00	0.03	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product37	SAMSUNG	GALAXYAL	0.22	0.32	0.00	0.35	0.06	0.02	0.00	0.04	0.06	0.06	0.02	0.00	0.03	0.00	0.00	0.11	0.18	0.11	0.01	0.02	0.04	(1.46)	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product38	SAMSUNG	GALAXYS6	0.21	0.29	0.00	0.50	0.06	0.02	0.00	0.04	0.08	0.11	0.02	0.00	0.05	0.00	0.00	0.12	0.26	0.15	0.01	0.03	0.05	0.01	(13.34)	0.03	0.00	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product40	SAMSUNG	GALAXYS6	0.21	0.27	0.00	0.51	0.06	0.02	0.00	0.04	0.08	0.11	0.02	0.00	0.05	0.00	0.00	0.11	0.28	0.15	0.01	0.03	0.05	0.01	0.04	(9.88)	0.00	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product42	SAMSUNG	GALAXYS4	0.19	0.19	0.00	0.18	0.05	0.02	0.00	0.03	0.03	0.03	0.01	0.00	0.01	0.00	0.00	0.11	0.12	0.06	0.01	0.01	0.02	0.00	0.01	0.01	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product44	SAMSUNG	GALAXYNC	0.22	0.31	0.00	0.28	0.06	0.02	0.00	0.04	0.06	0.04	0.01	0.00	0.02	0.00	0.00	0.12	0.25	0.14	0.01	0.03	0.05	0.00	0.03	0.02	0.00	(12.66)	0.00	0.01	0.00	0.00	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product49	SAMSUNG	GALAXYA7	0.19	0.23	0.00	0.19	0.05	0.02	0.00	0.03	0.04	0.03	0.01	0.00	0.01	0.00	0.00	0.12	0.14	0.08	0.01	0.02	0.03	0.00	0.01	0.01	0.00	0.00	(1.78)	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product52	SONY	XPERIAZ3N	0.20	0.26	0.00	0.21	0.05	0.02	0.00	0.03	0.04	0.03	0.01	0.00	0.01	0.00	0.00	0.12	0.16	0.09	0.01	0.02	0.03	0.00	0.02	0.01	0.00	0.00	0.00	(4.71)	0.00	0.00	0.01	0.00	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product54	SONY	XPERIAZ2N	0.19	0.20	0.00	0.17	0.05	0.02	0.00	0.03	0.03	0.03	0.01	0.00	0.01	0.00	0.00	0.12	0.11	0.06	0.01	0.01	0.02	0.00	0.01	0.01	0.00	0.00	0.00	0.00	(1.38)	0.00	0.01	0.00	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product62	HTC	ONE32GB	0.20	0.24	0.00	0.30	0.06	0.02	0.00	0.03	0.05	0.06	0.01	0.00	0.03	0.00	0.00	0.11	0.24	0.13	0.01	0.03	0.04	0.00	0.03	0.02	0.00	0.00	0.00	0.00	0.00	1.25	0.00	0.01	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product63	HTC	ONEM816	0.20	0.25	0.00	0.21	0.05	0.02	0.00	0.03	0.04	0.03	0.01	0.00	0.01	0.00	0.00	0.12	0.15	0.08	0.01	0.02	0.03	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	(4.94)	0.00	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00
		product67	HTC	ONEM932	0.22	0.33	0.00	0.34	0.06	0.02	0.00	0.04	0.06	0.05	0.02	0.00	0.02	0.00	0.00	0.12	0.20	0.12	0.01	0.02	0.04	0.00	0.03	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.01	(9.39)	0.00	(0.00)	0.00	0.00	0.01	0.00	0.00
		product70	HTC	ONEM8S1	0.17	0.20	0.00	0.18	0.05	0.02	0.00	0.03	0.03	0.03	0.01	0.00	0.01	0.00	0.00	0.11	0.13	0.07	0.01	0.01	0.02	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.58)	(0.00)	0.00	0.00	0.00	0.00	0.00
		product72	NOKIA	LUMIA930	0.20	0.26	0.00	0.31	0.05	0.02	0.00	0.04	0.05	0.06	0.01	0.00	0.03	0.00	0.00	0.11	0.24	0.13	0.01	0.03	0.04	0.00	0.03	0.02	0.00	0.00	0.00	0.00	0.00	(0.00)	0.00	0.01	0.00	0.25	(0.00)	0.00	0.01	0.00	0.00
		product74	NOKIA	LUMIA102	0.18	0.25	0.00	0.33	0.05	0.02	0.00	0.03	0.05	0.06	0.01	0.00	0.03	(0.00)	0.00	0.08	0.18	0.10	0.01	0.02	0.03	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	(0.00)	0.00	0.00	0.00	(0.00)	2.35	0.00	0.01	0.00	0.00
		product78	LG	D855G316	0.19	0.20	0.00	0.17	0.05	0.02	0.00	0.03	0.03	0.03	0.01	0.00	0.01	0.00	0.00	0.12	0.12	0.06	0.01	0.02	0.02	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.00	(0.90)	0.00	0.00	0.00
		product80	LG	H815G432	0.20	0.26	0.00	0.29	0.06	0.02	0.00	0.04	0.05	0.05	0.01	0.00	0.02	0.00	0.00	0.12	0.28	0.15	0.01	0.03	0.05	0.00	0.03	0.03	0.00	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	0.00	(2.28)	0.00	0.00
		product83	LG	D855G332	0.21	0.26	0.00	0.27	0.06	0.02	0.00	0.04	0.05	0.05	0.01	0.00	0.02	0.00	0.00	0.12	0.28	0.15	0.01	0.03	0.05	0.00	0.03	0.03	0.00	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	0.00	0.01	(2.93)	0.00
		product98	HUAWEI	ASCENDM	0.18	0.22	0.00	0.18	0.05	0.02	0.00	0.03	0.03	0.03	0.01	0.00	0.01	0.00	0.00	0.12	0.13	0.07	0.01	0.02	0.02	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.00	0.00	0.00	(0.75)

Table 27 Cross product-price elasticities of some products, Czech Republic

		cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI																										
		Min	(19.28)		Min	(19.28)	Min	(15.65)	Min	(6.67)	Min	(8.18)	Min	(0.30)	Min	(2.02)	Min	(1.50)																									
		Max	1.95		Max	(1.06)	Max	1.95	Max	(0.65)	Max	1.52	Max	1.34	Max	2.33	Max	(1.50)																									
		Avg	(6.88)		Avg	(7.77)	Avg	(7.51)	Avg	(3.66)	Avg	(3.86)	Avg	0.52	Avg	(0.24)	Avg	(1.50)																									
All	Czech Rep.	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20	21	24	25	27	28	30	36	37	38	40	42	44	49	52	54	62	63	67	70	72	74	78	80	83	98
Min	(19.28)	product01	APPLE	IPHONE5S	(4.26)	0.09	0.00	0.11	0.03	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.04	0.03	0.02	0.01	0.01	0.01	0.00	0.02	0.01	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	0.00	(0.00)	0.01	0.00	0.00
Max	2.33	product02	APPLE	IPHONE61	0.06	(8.53)	0.00	0.11	0.03	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.01	(0.00)	0.00	0.04	0.03	0.02	0.01	0.01	0.01	0.00	0.02	0.01	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	0.00	(0.00)	0.01	0.00	0.00
Avg	(0.14)	product04	APPLE	IPHONE51	0.05	0.07	(1.48)	0.08	0.02	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.04	0.03	0.02	0.01	0.01	0.01	0.00	0.02	0.01	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	0.00	(0.00)	0.01	0.00	0.00
		product05	APPLE	IPHONE66	0.07	0.11	0.00	(12.17)	0.05	0.01	0.00	0.01	0.04	0.06	0.02	0.00	0.02	0.00	0.00	0.04	0.04	0.02	0.01	0.02	0.01	0.01	0.05	0.03	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	(0.00)	(0.00)	0.02	0.00	0.00
		product08	APPLE	IPHONE5S	0.07	0.12	0.00	0.17	(7.55)	0.01	0.00	0.01	0.03	0.04	0.01	0.00	0.01	(0.00)	0.00	0.04	0.03	0.02	0.01	0.01	0.01	0.01	0.03	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	0.00	(0.00)	0.01	0.00	0.00
		product10	APPLE	IPHONE5C	0.06	0.08	0.00	0.10	0.03	(2.33)	0.00	0.01	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.04	0.03	0.02	0.01	0.01	0.01	0.00	0.02	0.01	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	0.00	(0.00)	0.01	0.00	0.00
		product11	APPLE	IPHONE53	0.06	0.09	0.00	0.16	0.04	0.01	(2.25)	0.01	0.03	0.04	0.01	0.00	0.02	(0.00)	0.00	0.04	0.03	0.02	0.01	0.02	0.01	0.01	0.04	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product12	APPLE	IPHONE6P	0.05	0.09	0.00	0.08	0.02	0.01	0.00	(11.11)	0.02	0.01	0.01	0.00	0.01	(0.00)	0.00	0.05	0.04	0.04	0.01	0.02	0.01	0.00	0.04	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	(0.00)	0.00	(0.00)	0.03	0.00	0.00
		product14	APPLE	IPHONE6P	0.06	0.09	0.00	0.16	0.04	0.01	0.00	0.02	(16.25)	0.04	0.02	0.00	0.02	(0.00)	0.00	0.04	0.05	0.04	0.01	0.02	0.01	0.01	0.06	0.03	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	0.00	0.00	(0.00)	0.02	0.00	0.00
		product16	APPLE	IPHONE61	0.07	0.10	0.00	0.28	0.05	0.01	0.00	0.01	0.05	(14.67)	0.03	0.00	0.04	0.00	0.00	0.03	0.05	0.03	0.02	0.02	0.01	0.01	0.07	0.05	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	(0.00)	(0.00)	0.02	0.01	0.00
		product17	APPLE	IPHONE5S	0.07	0.11	0.00	0.24	0.05	0.01	0.00	0.01	0.04	0.06	(11.08)	0.00	0.03	(0.00)	0.00	0.04	0.04	0.02	0.01	0.02	0.01	0.01	0.05	0.03	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product18	APPLE	IPHONE56	0.06	0.09	0.00	0.23	0.05	0.01	0.00	0.01	0.04	0.07	0.02	(2.86)	0.03	0.00	0.00	0.03	0.04	0.02	0.01	0.02	0.01	0.01	0.06	0.04	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	(0.00)	(0.00)	0.02	0.00	0.00
		product19	APPLE	IPHONE6P	0.06	0.08	0.00	0.24	0.05	0.01	0.00	0.01	0.05	0.09	0.03	0.00	(19.28)	0.00	0.00	0.03	0.06	0.04	0.02	0.03	0.01	0.01	0.09	0.05	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	0.00	(0.00)	(0.00)	0.03	0.01	0.00
		product20	APPLE	IPHONE4S	0.07	0.09	0.00	0.24	0.05	0.01	0.00	0.01	0.04	0.07	0.02	0.00	0.03	(1.06)	0.00	0.03	0.04	0.02	0.01	0.02	0.01	0.01	0.05	0.03	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	(0.00)	(0.00)	0.02	0.00	0.00
		product21	APPLE	IPHONE5C	0.07	0.11	0.00	0.17	0.04	0.01	0.00	0.01	0.03	0.04	0.01	0.00	0.01	(0.00)	(5.79)	0.04	0.03	0.02	0.01	0.01	0.01	0.01	0.03	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product24	SAMSUNG	GALAXYS5	0.05	0.06	0.00	0.05	0.02	0.01	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.00	0.00	(3.74)	0.05	0.04	0.01	0.02	0.01	0.00	0.04	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	(0.00)	0.00	(0.01)	0.04	0.00	0.00
		product25	SAMSUNG	GALAXYS6	0.05	0.06	0.00	0.07	0.02	0.01	0.00	0.02	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.04	(7.46)	0.07	0.01	0.05	0.02	0.00	0.08	0.05	(0.00)	0.00	0.00	0.02	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	(0.02)	0.07	0.00	0.00
		product27	SAMSUNG	GALAXYS6	0.05	0.07	0.00	0.07	0.02	0.01	0.00	0.02	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.05	0.09	(12.90)	0.01	0.04	0.02	0.00	0.07	0.04	(0.00)	0.00	0.00	0.02	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	(0.01)	0.06	0.00	0.00
		product28	SAMSUNG	GALAXYNC	0.05	0.06	0.00	0.08	0.02	0.01	0.00	0.02	0.03	0.02	0.01	0.00	0.01	(0.00)	0.00	0.04	0.07	0.05	(3.25)	0.04	0.02	0.00	0.06	0.04	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	(0.01)	0.05	0.00	0.00
		product30	SAMSUNG	GALAXYNC	0.05	0.06	0.00	0.07	0.02	0.01	0.00	0.02	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.05	0.10	0.07	0.01	(8.33)	0.02	0.00	0.08	0.05	(0.00)	0.00	0.00	0.02	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	(0.02)	0.07	0.00	0.00
		product36	SAMSUNG	GALAXYS6	0.05	0.06	0.00	0.07	0.02	0.01	0.00	0.02	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.05	0.09	0.06	0.01	0.04	(12.39)	0.00	0.07	0.04	(0.00)	0.00	0.00	0.02	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	(0.01)	0.07	0.00	0.00
		product37	SAMSUNG	GALAXYAL	0.06	0.09	0.00	0.14	0.03	0.01	0.00	0.01	0.03	0.03	0.01	0.00	0.01	(0.00)	0.00	0.04	0.04	0.02	0.01	0.02	0.01	(1.64)	0.04	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	0.00	(0.00)	0.02	0.00	0.00
		product38	SAMSUNG	GALAXYS6	0.05	0.06	0.00	0.12	0.03	0.01	0.00	0.02	0.04	0.04	0.02	0.00	0.02	0.00	0.00	0.04	0.09	0.06	0.01	0.04	0.02	0.00	(15.65)	0.06	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	(0.01)	0.06	0.00	0.00
		product40	SAMSUNG	GALAXYS6	0.05	0.06	0.00	0.13	0.03	0.01	0.00	0.02	0.04	0.04	0.02	0.00	0.02	0.00	0.00	0.04	0.10	0.07	0.01	0.05	0.02	0.01	0.10	(11.93)	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	(0.00)	(0.02)	0.07	0.00	0.00
		product42	SAMSUNG	GALAXYS4	0.04	0.05	0.00	0.05	0.02	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.03	0.05	0.03	0.01	0.02	0.01	0.00	0.04	0.02	1.95	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	(0.00)	(0.00)	(0.01)	0.03	0.00	0.00
		product44	SAMSUNG	GALAXYNC	0.05	0.07	0.00	0.07	0.02	0.01	0.00	0.02	0.03	0.02	0.01	0.00	0.01	0.00	0.00	0.05	0.08	0.06	0.01	0.04	0.02	0.00	0.07	0.04	(0.00)	(13.38)	0.00	0.02	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	(0.01)	0.06	0.00	0.00
		product49	SAMSUNG	GALAXYA7	0.05	0.06	0.00	0.06	0.02	0.01	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.04	0.05	0.04	0.01	0.03	0.01	0.00	0.04	0.03	(0.00)	0.00	(1.37)	0.01	0.00	(0.00)	0.01	0.00	0.00	(0.00)	0.00	(0.01)	0.04	0.00	0.00
		product52	SONY	XPERIAZ3N	0.05	0.07	0.00	0.06	0.02	0.01	0.00	0.02	0.02	0.01	0.01	0.00	0.01	(0.00)	0.00	0.04	0.05	0.04	0.01	0.03	0.01	0.00	0.04	0.02	(0.00)	0.00	0.00	(6.67)	0.00	(0.00)	0.01	0.00	0.00	(0.00)	0.00	(0.01)	0.03	0.00	0.00
		product54	SONY	XPERIAZ2N	0.04	0.05	0.00	0.04	0.02	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.04	0.04	0.03	0.01	0.02	0.01	0.00	0.03	0.02	(0.00)	0.00	0.00	0.01	(0.65)	(0.00)	0.01	0.00	0.00	(0.00)	0.00	(0.01)	0.02	(0.00)	0.00
		product62	HTC	ONE32GB	0.05	0.05	0.00	0.09	0.02	0.01	0.00	0.01	0.02	0.03	0.01	0.00	0.02	0.00	0.00	0.04	0.08	0.06	0.01	0.04	0.02	0.00	0.07	0.05	(0.00)	0.00	0.00	0.01	0.00	1.52	0.01	0.01	0.00	(0.00)	(0.00)	(0.01)	0.06	0.00	0.00
		product63	HTC	ONEM816	0.05	0.07	0.00	0.07	0.02	0.01	0.00	0.02	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.04	0.05	0.04	0.01	0.03	0.01	0.00	0.04	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	(5.81)	0.00	0.00	(0.00)	0.00	(0.01)	0.03	0.00	0.00
		product67	HTC	ONEM932	0.05	0.08	0.00	0.09	0.03	0.01	0.00	0.02	0.03	0.02	0.01	0.00	0.01	(0.00)	0.00	0.04	0.06	0.04	0.01	0.03	0.02	0.00	0.06	0.03	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	(8.18)	0.00	(0.00)	0.00	(0.01)	0.03	0.00	0.00
		product70	HTC	ONEM8S1	0.04	0.06	0.00	0.04	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.04	0.04	0.02	0.01	0.02	0.01	0.00	0.03	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	(2.99)	(0.00)	0.00	(0.00)	0.03	0.00	0.00
		product72	NOKIA	LUMIA930	0.05	0.06	0.00	0.09	0.02	0.01	0.00	0.01	0.03	0.03	0.01	0.00	0.01	0.00	0.00	0.04	0.08	0.05	0.01	0.04	0.02	0.00	0.07	0.04	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.30)	(0.00)	(0.01)	0.06	0.00	0.00
		product74	NOKIA	LUMIA102	0.05	0.08	0.00	0.13	0.03	0.01	0.00	0.01	0.03	0.03	0.01	0.00	0.02	(0.00)	0.00	0.03	0.04	0.03	0.01	0.02	0.01	0.00	0.04	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	0.00	1.34	(0.00)	0.02	0.00	0.00
		product78	LG	D855G316	0.03	0.03	0.00	0.03	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.03	0.07	0.04	0.01	0.03	0.01	0.00	0.04	0.03	(0.00)	0.00	0.00	0.01	(0.00)	(0.00)	0.00	0.00	0.00	(0.00)	(0.00)	2.33	0.03	(0.00)	0.00
		product80	LG	H815G432	0.05	0.05	0.00	0.08	0.02	0.01	0.00	0.02	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.04	0.11	0.07	0.01	0.05	0.02	0.00	0.09	0.05	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	0.00	(0.02)	(2.02)	0.00	0.00
		product83	LG	D855G332	0.05	0.05	0.00	0.07	0.02	0.01	0.00	0.01	0.02	0.02	0.01	0.00	0.01	0.00	0.00	0.04	0.11	0.07	0.01	0.05	0.02	0.00	0.09	0.06	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.01	0.00	(0.00)	(0.00)	(0.02)	0.08	(1.02)	0.00
		product98	HUAWEI	ASCENDM	0.05	0.06	0.00	0.06	0.02	0.01	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.04	0.05	0.04	0.01	0.03	0.01	0.00	0.04	0.02	(0.00)	0.00	0.00	0.01	0.00	(0.00)	0.01	0.00	0.00	(0.00)	0.00	(0.01)	0.04	0.00	(1.50)

Table 28 Cross product-price elasticities of some products, Poland

		cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI																										
		Min	(20.35)		Min	(20.35)	Min	(13.18)	Min	(4.73)	Min	(9.04)	Min	(0.61)	Min	(3.36)	Min	(0.98)																									
		Max	3.25		Max	(1.20)	Max	3.25	Max	(1.64)	Max	2.20	Max	2.22	Max	1.80	Max	(0.98)																									
		Avg	(7.12)		Avg	(9.33)	Avg	(5.64)	Avg	(3.19)	Avg	(4.98)	Avg	0.81	Avg	(0.88)	Avg	(0.98)																									
All	Poland	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20	21	24	25	27	28	30	36	37	38	40	42	44	49	52	54	62	63	67	70	72	74	78	80	83	98
Min	(20.35)	product01	APPLE	IPHONE5S	(6.68)	0.06	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.04	0.03	0.01	0.02	0.01	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.00	0.01	0.00	0.00	(0.00)	(0.01)	0.01	0.00	0.00
Max	3.25	product02	APPLE	IPHONE61	0.05	(10.35)	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.04	0.03	0.01	0.02	0.01	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	(0.01)	0.01	0.00	0.00
Avg	(0.15)	product04	APPLE	IPHONE51	0.04	0.04	(4.02)	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.02	0.02	0.00	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.02	0.01	0.00	0.01	0.01	0.02	0.00	(0.00)	(0.01)	0.00	0.00	0.00
		product05	APPLE	IPHONE66	0.04	0.03	0.00	(14.55)	0.02	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.05	0.04	0.01	0.02	0.02	0.00	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product08	APPLE	IPHONE5S	0.04	0.03	0.00	0.07	(9.12)	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.05	0.04	0.01	0.02	0.02	0.00	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product10	APPLE	IPHONE5C	0.04	0.04	0.00	0.01	0.00	(1.20)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.02	0.02	0.01	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.01	0.01	0.01	0.00	(0.00)	(0.01)	0.00	0.00	0.00
		product11	APPLE	IPHONE53	0.03	0.04	0.00	0.03	0.01	0.00	(3.22)	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	0.03	0.01	0.02	0.01	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.01	0.01	0.01	0.00	(0.00)	(0.01)	0.01	0.00	0.00
		product12	APPLE	IPHONE6P	0.05	0.05	0.00	0.02	0.01	0.00	0.00	(14.58)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.04	0.04	0.01	0.02	0.02	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.00	0.01	0.00	0.00	(0.00)	(0.01)	0.01	0.00	0.00
		product14	APPLE	IPHONE6P	0.04	0.03	0.00	0.07	0.01	0.00	0.00	0.01	(17.05)	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.06	0.05	0.01	0.03	0.02	0.00	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product16	APPLE	IPHONE61	0.03	0.03	0.00	0.09	0.01	0.00	0.00	0.01	0.01	(17.12)	0.00	0.00	0.01	0.00	0.00	0.02	0.05	0.04	0.01	0.02	0.02	0.00	0.01	0.01	(0.00)	0.00	(0.00)	0.00	0.01	(0.00)	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product17	APPLE	IPHONE5S	0.04	0.04	0.00	0.08	0.02	0.00	0.00	0.01	0.01	0.01	(12.53)	0.00	0.00	0.00	0.00	0.03	0.05	0.04	0.01	0.02	0.02	0.00	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product18	APPLE	IPHONE56	0.03	0.03	0.00	0.07	0.01	0.00	0.00	0.01	0.01	0.01	0.00	(6.86)	0.01	0.00	0.00	0.02	0.04	0.03	0.01	0.02	0.02	(0.00)	0.01	0.00	(0.00)	0.00	(0.00)	0.01	0.00	(0.00)	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product19	APPLE	IPHONE6P	0.03	0.03	0.00	0.08	0.01	0.00	0.00	0.01	0.01	0.02	0.00	0.00	(20.35)	0.00	0.00	0.02	0.05	0.04	0.01	0.02	0.02	0.00	0.01	0.01	(0.00)	0.00	(0.00)	0.00	0.01	(0.00)	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product20	APPLE	IPHONE4S	0.04	0.03	0.00	0.08	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	(3.57)	0.00	0.02	0.05	0.04	0.01	0.02	0.02	(0.00)	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product21	APPLE	IPHONE5C	0.04	0.05	0.00	0.03	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	(6.22)	0.02	0.04	0.04	0.01	0.02	0.02	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.00	0.01	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product24	SAMSUNG	GALAXYS5	0.04	0.05	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(1.85)	0.03	0.03	0.01	0.02	0.01	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.01	0.01	0.01	0.00	(0.00)	(0.01)	0.01	0.00	0.00
		product25	SAMSUNG	GALAXYS6	0.04	0.04	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	(6.07)	0.06	0.01	0.04	0.03	0.00	0.01	0.01	(0.00)	0.01	(0.00)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	(0.00)	0.00
		product27	SAMSUNG	GALAXYS6	0.04	0.04	0.00	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.08	(10.20)	0.01	0.03	0.03	0.00	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.01	0.00	0.00	0.01	0.00	0.00	(0.00)	(0.00)	0.01	(0.00)	0.00
		product28	SAMSUNG	GALAXYNC	0.04	0.03	0.00	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.08	0.06	(1.78)	0.04	0.03	0.00	0.01	0.00	(0.00)	0.01	(0.00)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product30	SAMSUNG	GALAXYNC	0.04	0.03	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.09	0.06	0.01	(6.97)	0.03	0.00	0.01	0.01	(0.00)	0.01	(0.00)	0.00	0.01	(0.00)	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.02	(0.00)	0.00
		product36	SAMSUNG	GALAXYS6	0.04	0.03	0.00	0.03	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.08	0.06	0.01	0.04	(11.68)	0.00	0.01	0.00	(0.00)	0.01	(0.00)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product37	SAMSUNG	GALAXYAL	0.03	0.03	0.00	0.03	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.04	0.01	0.02	0.02	(0.12)	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.01)	0.01	0.00	0.00
		product38	SAMSUNG	GALAXYS6	0.04	0.03	0.00	0.03	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.08	0.06	0.01	0.04	0.03	0.00	(13.18)	0.01	(0.00)	0.01	(0.00)	0.00	0.01	(0.00)	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.01	0.00	0.00
		product40	SAMSUNG	GALAXYS6	0.03	0.03	0.00	0.03	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.09	0.06	0.01	0.04	0.03	0.00	0.01	(9.89)	(0.00)	0.01	(0.00)	0.00	0.01	(0.00)	0.00	0.00	0.00	0.00	(0.00)	(0.00)	0.02	0.00	0.00
		product42	SAMSUNG	GALAXYS4	0.03	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.04	0.00	0.02	0.02	(0.00)	0.00	0.00	3.25	0.00	(0.00)	0.01	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.01)	0.01	(0.00)	0.00
		product44	SAMSUNG	GALAXYNC	0.04	0.04	0.00	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.08	0.06	0.01	0.03	0.03	0.00	0.01	0.00	(0.00)	(10.69)	(0.00)	0.00	0.01	0.00	0.00	0.01	0.00	0.00	(0.00)	(0.00)	0.01	(0.00)	0.00
		product49	SAMSUNG	GALAXYA7	0.03	0.03	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.06	0.05	0.01	0.03	0.02	0.00	0.01	0.00	(0.00)	0.00	1.45	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.01)	0.01	0.00	0.00
		product52	SONY	XPERIAZ3N	0.03	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)	0.00	(0.00)	(4.73)	0.01	0.00	0.01	0.01	0.03	0.00	0.00	(0.01)	0.00	0.00	0.00
		product54	SONY	XPERIAZ2N	0.04	0.04	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.04	0.03	0.01	0.02	0.01	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	(1.64)	0.00	0.01	0.01	0.01	0.00	(0.00)	(0.01)	0.01	(0.00)	0.00
		product62	HTC	ONE32GB	0.02	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.03	0.00	0.02	0.01	(0.00)	0.00	0.00	(0.00)	0.00	(0.00)	0.03	0.00	2.20	0.01	0.00	0.02	0.00	(0.00)	(0.01)	0.01	(0.00)	0.00
		product63	HTC	ONEM816	0.03	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.01	0.00	0.01	0.00	(0.00)	0.00	0.00	(0.00)	0.00	(0.00)	0.04	0.01	0.01	(4.35)	0.01	0.02	0.00	(0.00)	(0.01)	0.00	0.00	0.00
		product67	HTC	ONEM932	0.04	0.05	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.04	0.03	0.01	0.02	0.01	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.00	(8.75)	0.01	0.00	(0.00)	(0.01)	0.01	0.00	0.00
		product70	HTC	ONEM8S1	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	(0.00)	0.00	0.00	(0.00)	0.00	(0.00)	0.06	0.01	0.01	0.02	0.01	(9.04)	0.00	0.00	(0.01)	0.00	0.00	0.00
		product72	NOKIA	LUMIA930	0.03	0.03	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.04	0.01	0.02	0.02	(0.00)	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.00	0.00	0.00	(0.61)	(0.00)	(0.01)	0.01	0.00	0.00
		product74	NOKIA	LUMIA102	0.03	0.02	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.04	0.01	0.02	0.02	(0.00)	0.01	0.00	(0.00)	0.00	(0.00)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.22	(0.00)	0.01	0.00	0.00
		product78	LG	D855G316	0.03	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.03	0.02	0.00	0.01	0.01	(0.00)	0.00	0.00	(0.00)	0.00	(0.00)	0.02	0.01	0.00	0.01	0.01	0.01	0.00	(0.00)	1.80	0.01	0.00	0.00
		product80	LG	H815G432	0.04	0.03	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.08	0.06	0.01	0.04	0.03	0.00	0.01	0.00	(0.00)	0.01	(0.00)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(0.00)	(0.01)	(3.36)	0.00	0.00
		product83	LG	D855G332	0.03	0.03	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.09	0.06	0.01	0.04	0.03	0.00	0.01	0.01	(0.00)	0.01	(0.00)	0.00	0.01	(0.00)	0.00	0.00	0.00	0.00	(0.00)	(0.01)	0.02	(1.07)	0.00
		product98	HUAWEI	ASCENDM	0.04	0.05	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.04	0.01	0.02	0.02	0.00	0.00	0.00	(0.00)	0.00	(0.00)	0.01	0.01	0.00	0.00	0.01	0.00	0.00	(0.00)	(0.01)	0.01	(0.00)	(0.98)

Table 29 Cross product-price elasticities of some products, Portugal

		cross			APPLE		SAMSUNG		SONY		HTC		NOKIA		LG		HUAWEI																										
		Min	(20.21)		Min	(20.21)	Min	(14.72)	Min	(5.73)	Min	(7.35)	Min	(1.86)	Min	(4.68)	Min	(1.40)																									
		Max	0.90		Max	0.23	Max	0.55	Max	(3.48)	Max	0.90	Max	0.48	Max	(0.85)	Max	(1.40)																									
		Avg	(7.47)		Avg	(8.86)	Avg	(7.76)	Avg	(4.60)	Avg	(3.36)	Avg	(0.69)	Avg	(2.34)	Avg	(1.40)																									
ALL	Portugal	Product	Brand	Model1	1	2	4	5	8	10	11	12	14	16	17	18	19	20	21	24	25	27	28	30	36	37	38	40	42	44	49	52	54	62	63	67	70	72	74	78	80	83	98
Min	(20.21)	product01	APPLE	IPHONE5S	(6.10)	0.15	0.00	0.10	0.02	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.05	0.05	0.01	0.03	0.03	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	0.90	product02	APPLE	IPHONE61	0.05	(8.52)	0.00	0.09	0.02	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.05	0.05	0.02	0.04	0.03	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Avg	(0.15)	product04	APPLE	IPHONE51	0.04	0.08	(0.90)	0.05	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.04	0.04	0.03	0.01	0.02	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		product05	APPLE	IPHONE66	0.06	0.15	0.00	(12.42)	0.03	0.00	0.00	0.03	0.05	0.04	0.01	0.00	0.04	0.00	0.01	0.04	0.09	0.06	0.02	0.04	0.04	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
		product08	APPLE	IPHONE5S	0.06	0.17	0.00	0.15	(9.22)	0.00	0.00	0.03	0.03	0.02	0.01	0.00	0.02	0.00	0.01	0.04	0.07	0.05	0.02	0.04	0.03	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
		product10	APPLE	IPHONE5C	0.04	0.09	0.00	0.07	0.01	(1.76)	0.00	0.02	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.04	0.05	0.04	0.01	0.03	0.03	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		product11	APPLE	IPHONE53	0.05	0.15	0.00	0.09	0.02	0.00	(6.03)	0.03	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.05	0.05	0.05	0.02	0.03	0.03	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		product12	APPLE	IPHONE6P	0.05	0.13	0.00	0.07	0.01	0.00	0.00	(11.94)	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.07	0.07	0.02	0.04	0.05	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product14	APPLE	IPHONE6P	0.06	0.13	0.00	0.21	0.03	0.00	0.00	0.03	(16.16)	0.03	0.01	0.00	0.03	0.00	0.01	0.04	0.10	0.08	0.02	0.05	0.05	0.02	0.02	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product16	APPLE	IPHONE61	0.06	0.13	0.00	0.35	0.03	0.00	0.00	0.02	0.07	(15.06)	0.01	0.00	0.06	0.00	0.01	0.03	0.11	0.05	0.02	0.04	0.04	0.02	0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
		product17	APPLE	IPHONE5S	0.06	0.16	0.00	0.19	0.03	0.00	0.00	0.03	0.04	0.03	(15.45)	0.00	0.02	0.00	0.01	0.05	0.07	0.06	0.02	0.04	0.04	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
		product18	APPLE	IPHONE56	0.06	0.14	0.00	0.23	0.03	0.00	0.00	0.02	0.05	0.04	0.01	(6.87)	0.03	0.00	0.01	0.03	0.09	0.05	0.02	0.04	0.04	0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
		product19	APPLE	IPHONE6P	0.06	0.12	0.00	0.33	0.03	0.00	0.00	0.02	0.06	0.07	0.01	0.00	(20.21)	0.00	0.01	0.03	0.12	0.07	0.02	0.05	0.05	0.01	0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
		product20	APPLE	IPHONE4S	0.05	0.13	0.00	0.24	0.03	0.00	0.00	0.02	0.05	0.04	0.01	0.00	0.04	0.23	0.01	0.03	0.09	0.05	0.01	0.04	0.03	0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
		product21	APPLE	IPHONE5C	0.05	0.15	0.00	0.13	0.02	0.00	0.00	0.03	0.03	0.02	0.01	0.00	0.01	0.00	(6.06)	0.05	0.06	0.05	0.02	0.04	0.03	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		product24	SAMSUNG	GALAXYS5	0.04	0.08	0.00	0.04	0.01	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	(5.35)	0.06	0.06	0.02	0.03	0.04	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product25	SAMSUNG	GALAXYS6	0.04	0.09	0.00	0.09	0.01	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.04	(6.03)	0.12	0.02	0.06	0.08	0.01	0.02	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.01	(0.00)	0.00
		product27	SAMSUNG	GALAXYS6	0.04	0.10	0.00	0.07	0.01	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.11	(10.56)	0.02	0.06	0.07	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.01	(0.00)	0.00
		product28	SAMSUNG	GALAXYNC	0.04	0.10	0.00	0.06	0.01	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.09	0.09	(5.38)	0.05	0.06	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product30	SAMSUNG	GALAXYNC	0.05	0.10	0.00	0.07	0.01	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.11	0.12	0.02	(10.25)	0.08	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.01	(0.00)	0.00
		product36	SAMSUNG	GALAXYS6	0.05	0.10	0.00	0.07	0.01	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.11	0.11	0.02	0.06	(11.89)	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.01	(0.00)	0.00
		product37	SAMSUNG	GALAXYAL	0.05	0.13	0.00	0.10	0.02	0.00	0.00	0.03	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.04	0.07	0.06	0.01	0.04	0.04	(3.54)	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product38	SAMSUNG	GALAXYS6	0.05	0.10	0.00	0.15	0.02	0.00	0.00	0.03	0.04	0.03	0.00	0.00	0.03	0.00	0.00	0.04	0.13	0.12	0.02	0.06	0.08	0.01	(14.63)	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product40	SAMSUNG	GALAXYS6	0.05	0.09	0.00	0.19	0.02	0.00	0.00	0.02	0.04	0.03	0.00	0.00	0.03	0.00	0.00	0.04	0.15	0.12	0.02	0.07	0.08	0.01	0.03	(10.12)	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.01	(0.00)	0.00
		product42	SAMSUNG	GALAXYS4	0.04	0.06	0.00	0.05	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.04	0.05	0.05	0.01	0.03	0.03	0.01	0.01	0.01	0.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product44	SAMSUNG	GALAXYNC	0.05	0.11	0.00	0.06	0.01	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.10	0.11	0.02	0.06	0.07	0.01	0.02	0.01	0.00	(14.72)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product49	SAMSUNG	GALAXYA7	0.04	0.07	0.00	0.05	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.06	0.06	0.01	0.03	0.04	0.01	0.01	0.01	0.00	0.00	(1.15)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product52	SONY	XPERIAZ3N	0.04	0.09	0.00	0.04	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.05	0.06	0.07	0.02	0.04	0.04	0.01	0.01	0.01	0.00	0.00	0.00	(5.73)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product54	SONY	XPERIAZ2N	0.04	0.07	0.00	0.03	0.01	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.05	0.06	0.02	0.03	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	(3.48)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product62	HTC	ONE32GB	0.04	0.08	0.00	0.07	0.01	0.00	0.00	0.02	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.04	0.11	0.10	0.01	0.05	0.06	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.00	0.00	(0.00)	0.01	(0.00)	0.00
		product63	HTC	ONEM816	0.04	0.09	0.00	0.05	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.06	0.06	0.02	0.04	0.04	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	(6.56)	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product67	HTC	ONEM932	0.05	0.12	0.00	0.08	0.01	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.08	0.08	0.02	0.05	0.06	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	(7.35)	0.00	0.00	0.00	0.00	0.01	(0.00)	0.00
		product70	HTC	ONEM8S1	0.04	0.07	0.00	0.05	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.04	0.06	0.05	0.01	0.03	0.04	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.42)	0.00	0.00	0.00	0.01	(0.00)	0.00
		product72	NOKIA	LUMIA930	0.04	0.09	0.00	0.09	0.02	0.00	0.00	0.02	0.02	0.02	0.00	0.00	0.01	0.00	0.00	0.04	0.11	0.10	0.01	0.06	0.07	0.01	0.02	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(1.86)	0.00	(0.00)	0.01	(0.00)	0.00
		product74	NOKIA	LUMIA102	0.04	0.10	0.00	0.08	0.02	0.00	0.00	0.02	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.04	0.07	0.06	0.02	0.04	0.04	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.48	0.00	0.01	(0.00)	0.00
		product78	LG	D855G316	0.04	0.07	0.00	0.03	0.01	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.07	0.08	0.01	0.03	0.05	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(1.50)	0.01	(0.00)	0.00
		product80	LG	H815G432	0.04	0.09	0.00	0.07	0.01	0.00	0.00	0.03	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.04	0.12	0.12	0.02	0.06	0.08	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	(4.68)	(0.00)	0.00
		product83	LG	D855G332	0.04	0.08	0.00	0.07	0.01	0.00	0.00	0.02	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.04	0.12	0.12	0.01	0.06	0.07	0.01	0.02	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	(0.00)	0.01	(0.85)	0.00
		product98	HUAWEI	ASCENDM	0.04	0.08	0.00	0.05	0.01	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.05	0.06	0.06	0.01	0.03	0.04	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	(0.00)	(1.40)

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CAPÍTULO 4: Product characteristics-based forecast for MicroLED using machine learning models and ensemble techniques

Abstract

This paper proposes a smart approach based on a statistical algorithm and machine learning to predict product demand before launching based on the Bass model. First, we create product attributes and product diffusion databases and use them as input and output. We use statistical regression and machine learning algorithms, which can reliably map the relationship between traits and diffusion characteristics of existing products and, in turn, can predict the demand for new products. Then, we construct and evaluate a unique regression model that uses the product's properties to indicate the innovation and imitation coefficients, p and q, of the Bass model. Estimation of these coefficients using Look-like (comparative inference method) shows similar or lower prediction accuracy than the K-Nearest Neighbor (KNN) and LASSO Cross-Validation (LASSO CV). The Look-like process produces about twice as much error as the best linear multiple regression model among individual regression models. The prediction error is about ten times larger than the best ensemble regression model, Random Forest. This result indicates that our Bass Model parameter estimation framework using the Random Forest ensemble or Deep Learning is quite reliable.
Keywords

Product characteristics, demand forecast, diffusion models, Bass model, machine learning, ensemble techniques, deep learning

JEL Codes

C35, C45, C52, C53, C81, D12, D92, O33, O52

1. Introduction

Decision-makers in companies with a long term vision that focus on profit and growth have to deal with a fundamental dilemma. On the one hand, they must continually bring new products into the market since it is the way to increase their current sales and profit significantly. On the other hand, they usually need higher investment, and the risk of failure to address new market demands could constitute a danger for the company's survival. Therefore, companies launching new products always face quite a tricky dilemma. They have to not only decide the products to sell but also how and when to sell them. Therefore, a pre-launch demand forecast adds substantial value for decision-makers and many product and demand planning managers because they will be a reference point for product planning and decision making on deployment and promotions. This paper defines new products as 1) products that either never have existed before; 2) some variations of existing products or 3) products sold in other markets that are new to a specific market. Applying this, mainly industrial and technical definition, electronics products have various types of new products that would fit our three definitions or mix them (Garcia & Calantone, 2002). In the former case, the company must innovate and develop the entire market and only refer to similar products. In cases 2) and 3), the company also can conclude the experiences that another competitor has already had. Their strategy will be taking the market share of the pioneer through product differentiation and a war of prices.

In the new product development (NPD) literature, we observe some innovation diffusion elements: innovation, the social system, communication channels, and time (Singh, et al., 2012), and we find researchers combining qualitative and quantitative demand forecasting methods. It is convenient to use qualitative methods, especially for new products, which may give individual results in implementing models. As we can imagine, it is challenging to have a perfect model in all contexts- therefore, there are many attempts to mix methods to come up with alternative ways of arriving at a second best. In many studies, diffusion models with these curves then fitted using past data. A change's success is primarily determined by marketing communication during the diffusion process (Shavinina, 2003). The momentum slowly grows until it reaches the inflection point, then the speed of growth starts to decrease, and the market reaches saturation soon. Although many diffusion models are fully/ partially successful with structurally estimating the market and underlying parameters, they tend to be very rigid even when the demand structure changes fast. In other words, the model's long-term stability is difficult to predict, given the uncertainty of the predictions for individual independent variables. The Bass model has an intrinsic solution to this problem as long as we can extract non-linear relationships in the dataset by updating sales data for new items and adjusting our forecasts by minimizing the impact of the similarities found on our estimates.

We will start with the Bass model (Bass, 1969) for predicting the correct demand for new concepts and other things (such as technology, products) before their launching would give many advantages to policymakers and companies. The most representative diffusion model described above is the Bass model used to conduct product-specific diffusion analysis. There are many ways of formulating the Bass model. The innovation coefficient (p) captures the relative importance of innovative customers to generate revenue for the new product. The imitation coefficient (q) captures imitation customers' close essence in making sales for the new product. The model works in a way such that, regardless of the values of p and q, as more and more customers accept or buy the new product, the relative impact of mimicking customer purchases plays a more critical role in determining the sales curve.

The equation below requires a business owner or group of business owners to provide a single estimate of first-year sales and total sales for life (i.e., first-year adopters and accumulated adopters). Since few new products have had or have enjoyed monopoly status for a long time, managers need to estimate the total number of users in the product category in light of alternatives and competitive responses. The estimated parameters of p and q then give the following equation:

$$Q_t = p(M - A) + q(\frac{A}{M})(M - A) \quad \textbf{(1)}$$

Where M = Total number of potential buyers of the new product; A (N(t)) = Accumulated number of previous adopters; Q_t = number of adopters or units sold at time t; p = innovation coefficient (or the factor of external force) and q = imitation coefficient (or internal diffusion factor).

We can simplify equation (1) to:

$$Q_t = [p + q\left(\frac{A}{M}\right)](M - A) \quad \textbf{(2)}$$

Having set up the model structure and configuring input-output variables by defining a learning task, the next step is to set up appropriate seeking algorithms and to select proper performance criteria. Then, we choose useful algorithms: We construct a Bass parameter estimation model and use a total of 11 methods for regression, namely, three linear regressions, three non-linear models, four ensembles alternatives, and Deep Learning. First, we make estimates with ten algorithms, and we compare them with Deep Learning methods. The Bass model provides a good starting point for predicting the pattern of long-term sales of new technologies and new long-lasting products. The model uses three parameters, p, q, and m, and based on the assumption of two types of communication channels: mass communication (p = the innovation coefficient, external influence) and word of mouth (q = the imitation coefficient, internal force) a potential market size m. To obtain predictions for a variable (Y), we use given a set of k potential predictor variables plus the three parameters $\boldsymbol{X} = (x_1, x_2, \dots, x_k, p, q, m)$. p, q, and m are the Bass parameters and k the number of product attributes, and they will measure the similarities amount of products in the demand database. In our paper, we select k = 36, after the literature study and our experiment, which we will discuss at the end of this chapter.

The form of the linear multiple regression model for predicting a response Y is given by

$$Y = f(\boldsymbol{X}) + \epsilon = \beta_o + \beta_1 x_1 + \cdots + \beta_k x_k + \beta_p x_p + \beta_q x_q + \beta_m x_m + \epsilon \quad (3)$$

And the usual assumption is $Var(\epsilon) = \sigma^2$.

In matrix notation,

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{e} \quad \textbf{(1)}$$

where,

$$\boldsymbol{Y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_{n-1} \\ y_n \end{pmatrix}, \ \boldsymbol{X} = \begin{pmatrix} 1 & x_{11} & \cdots & x_{n,k} & x_{n,p} & x_{n,q} & x_{1,m} \\ 1 & x_{21} & \cdots & x_{n,k} & x_{n,p} & x_{n,q} & x_{2,m} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & \cdots & x_{n,k} & x_{n,p} & x_{n,q} & x_{n,m} \end{pmatrix}, \ \boldsymbol{\beta} = \begin{pmatrix} \beta_o \\ \beta_1 \\ \vdots \\ \beta_k \\ \beta_p \\ \beta_q \\ \beta_m \end{pmatrix} \ and \ \boldsymbol{e} = \begin{pmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{pmatrix}. \quad \textbf{(5)}$$

Here, n is the number of different products (n = 174 in our paper) in the product database.

After the literature study and gathering data, our first step to the implementation is obtaining as much as the Bass database; in the context of equation (5), the more n, the better and selecting and gathering optimal product attribute database in the context of equation (5), choosing the most appropriate k. We collect all available Bass model parameters from the literature and construct a product demand during the literature study at the preparation and data gathering stage. In our paper, we follow a three-fold approach in terms of building as much as possible n. First, we make the most demand database and market intelligence data in the context of (Lee, et al., 2014). We collected sales data from many associations and market intelligent databases and cleaned them for the analysis, then estimated m, p, q. We also summarize the results of a meta-analysis based on the Bass parameters from the literature. Finally, we performed three rounds of questionnaires to ask the Bass model's proxy parameters and possible product attributes. We need to determine the three parameters, m, p, and q in the Bass diffusion model for all n records. Applying Delphi methods qualitatively and sharing each round and data statistics results, we not only refined the Bass parameters. We also measured and defined the product attributes k of all n products from the industrial database containing annual sales data for all available products. As for the attribute database, we start constructing a product attribute database by defining key attributes that comprehensively explain a product's characteristics and assign appropriate values to each product aspect. Then we consolidate the Bass database with our product attribute database. As we will see, Machine Learning techniques provide us with several tools that researchers can use to summarize meaningfully different types of nonlinear relationships in the data (Varian, 2014).

Second, we utilize the database from the first step, the Bass model (m, p, q) with product attributes (k). We built various machine learning-based regression models using product attributes as inputs and the Bass diffusion model's two coefficients as objectives, based on the information stored in the product attribute database (a) and the product demand database (b). Then we identified significant product attributes for estimating the Bass diffusion model's coefficient and analyzing their influence on the prediction results. After evaluating parameters separately, we construct various forecast models for Bass model parameters. Namely, we want to apply and assess many machine learning methods and Deep Learning methods to get one of the best performing models. In this regard, we built many ensemble regression models by combining various regression methodologies. In theory, it is a well-known fact that the ensemble model has a better predictive performance than the single model and numerous empirical studies. We expect that the ensemble models have higher prediction accuracy than the unique optimal model. We use the Ensemble to overcome the shortcomings of individual regression algorithms and pursue more accurate prediction performance. Finally, we build deep learning models and compare our results with forecasts obtained using Google's Open source platform Tensorflow. In this context, we relatively low counts of n, Machine learning methods provide a reasonable basis for our type of task since mainly many machine learning can allow us to discover intrinsic, sometimes unforeseen, relationships between high-computing variables. We make the most of the collected and estimated parameters database by implementing a new approach using state-of-the-art machine learning open source libraries such as sci-kit-learn and Tensorflow. In this paper, we use 11 representative regression algorithms widely used in economics, statistics, and machine learning; namely Multiple linear regression (MLR), Ridge Regression, Lasso Regression, Classification and regression tree (CART), Random forests, AdaBoost, Gradient Boosting Regressors (GBR), Extreme Gradient Boosting Regressors (XGBR) and finally Deep learning: TensorFlow and Keras. We first make an estimation and perform evaluations of the different methods.

Finally, once we have our database, we conduct a case study using a new product (microLED); MicroLED is a new emerging display technology.- the display consists of rows of microscopic LEDs that form the individual pixel elements. Compared to widely used LCD technology, microLED offers better contrast, faster response times, and higher energy efficiency (Samsung, 2018). Then, we want to perform a pre-launch demand forecast for MicroLED based on the Bass model, combined with ML methods. We will identify various attributes as independent variables and estimate the coefficient of innovation p and diffusion q as dependent variables using the product demand database. The results will allow manufacturers to make strategic decisions for developing product marketing that enables product managers to simulate the television market's evolution, thus preparing them for launching products in the marketplace. The most challenging mission for adapting the Bass model for new products is estimating a new product's right parameters with little or no available historical sales data. The conventional approach to pre-launch forecasting is using analogs- or Look-like analysis. We use a similar product's lifecycle. We try to find out market share statistics with related products and their historical data. We also used the questionnaires' results to get the relevant attributes for all available products and Micro-LED vis-à-vis other products for the empirical application.

In this way, analyzing past groups' sales performance and conducting similarity studies on items in these collections will provide a powerful tool to predict sales of new products. Having defined the similarities, one can use qualitative methods to capture the demand trend based on a statistical analysis of market data from the past. After this phase, quantitative techniques could provide satisfactory results using much data for predictions. Section 5 shows a look-like analysis for MicroLED demand forecast mixing data from other products of the same category. Digital TV Sets & Monitors, Plasma DTV, Color TV, Projection TV, and LTV Flat), then extrapolate future sales of MicroLED products to show the differences in results. However, we all know that the new product will not have the same life cycle as the most similar product. Especially in our interest fields, namely, high technology fields, have significant characteristics from new products that are fundamentally very different from similar old products.

We can define and find similarities in many ways. One of the most effective ways would be to link new product forecasts with the products' historical data with attributes closely related to the latest developments during previous data collections. In this case, finding similarities throughout the many seemingly related and unrelated industries without considering these characteristics may not sufficiently capture all the forecasting procedure's complexity. Therefore there have been many approaches to measure those similarities quantitively and structurally. In (Lee, et al., 2014) and (Ganjeizadeh, et al. 2017), and many others, we find the concept of characteristics and product attributes where new products can inherit similar product characteristics' sales behavior. In this context, we will follow the ways proposed framework based on (Lee et al., 2006, and Lee et al., 2014). It is quite crucial to determine what the components are and how to measure the similarity.

The rest of the paper is as follows. Section 3 explains models' constructs and introduces various machine learning-based regression models using product attributes as inputs and the Bass diffusion model's three coefficients as objectives, namely, m, p, and q. Then, we show the product database building by defining the critical attributes of products that will measure the similarities amount of products in the demand database. Section 4 briefly shows p, q estimation results, using 11 machine learning bases methods and comparing their performances. In section 5, we use our database and methods to estimate Micro-LED demands empirically. Finally, in section 6, we aim to summarize many machine learning methods to determine coefficients and make an ensemble to make the most of each model. We will also discuss how our methodological framework in this paper overcomes earlier models' limitations, notably their inability to accommodate consumer heterogeneity and their inability to predict demand for new products reflecting the market's complexity.

2. Background

2.1. Consumer electronics industry and pre-launch demand forecast

Accurate demand estimation is a crucial determinant of new products' success because it affects competitiveness and profitability and provides essential information for purchasing, production and inventory levels, logistics, finance, or marketing decisions (Arvan, et al., 2019). Academics generally believe that we have begun to understand the process of developing and diffusing innovations, and they come with many names such as iPhones, industry 4.0, or any type of new product. In the economics and marketing literature, we can find plenty of traditional methods for the forecasts and demand estimation of existing products, starting from standard discrete choice models and more advanced proposals to relax some restrictions (Cho, 2019). In general, companies and researchers apply those methods to time series since they show a high degree of accuracy to historical sales data (Sadaei, et al., 2017). Regression analysis, logit models, historical trend smoothing, and time series stochastic models, among others, have been proposed and applied for demand estimation. These traditional techniques might not be the most appropriate options since they usually consider a linear relationship between inputs and outputs, which generally does not correspond to reality. In the consumer goods industry, where consumers make decisions daily and quickly, sales estimates are even more critical for companies (Martínez, et al., 2020). The innovation process is now a part of our lives for radical, incremental, really new, discontinuous, and imitative innovations and architectural, modular, improving, and evolutionary innovations. This fact is especially relevant for Consumer Electronics (CE), where it is fundamental that companies determine it for planning future investment, maintenance, and arranging resources (Hamzaçebi, 2016).

Due to rapid aging, many fast-moving consumer goods are short-lived (Cohen, et al., 2017). Moore's law still holds in the 21st century, and computing power grows simultaneously; of course, this provides tech companies more opportunities to develop ideas that make the most of these advances to attract more consumers. The CE market seems to be exploding accordingly. Experts expect annual global CE sales to reach $2.9 trillion by 2020 (Ltd. 2017). New products, such as smartphones, OLED TV, or cloud-computer, have evolved and will grow globally at high speed. Moreover, to attract consumers' tastes, CE companies are seeking new types of products. Nevertheless, many "brand new" products are somehow variations of existing products; many electronics conglomerates already have the technology to make any product that best fits customers' needs.

Consequently, goods such as electronics and tech products have short life cycles, are quickly outdated, updated frequently, and offer many competitive alternatives (Tarallo et al., 2019). From the demand side, the CE market changes drastically due to the changes in tastes and pricing; these products and substitutes' marketing activities will affect consumer decisions (Parniangtong, 2017). The crucial point is forecasting new CE product demand to understand the relationship between manufacturers' production decisions and dynamic consumer behavior. Moreover, with the advent of the internet and social media, new ideas are shared among consumers. They changed consumers' tastes drastically, and companies with new technologies are making these new products to meet customers' needs (De Mooij, 2004). It will also depend on the alternatives since, in many cases, the purchase means changing or upgrading existing products. Another factor that makes the demand forecasting more complicated is that consumers face intertemporal trade-offs (Foxall, 2010). Depending on the substitutes' saturation rate, many of those products are not purchased because customers already have alternatives, and the consumption pattern changes tastes or pricing (Einav & Levin, 2014). Because those predictive models are used to make economic decisions and policy changes, the results might not only be what the model predicts since the planning and choices about the products might already impact the underlying behavior generating the relationships in the data (Lucas, 1976). However, even if, to a certain extent, we can predict a significant diffusion mechanism and measure the possible diffusion curve.

2.2. Diffusion models

Diffusion is a fundamental process in economic environments (Rahmandad & Sterman, 2008). The term "diffusion" merges concepts such as contagion, imitation, social learning, structured dissemination, and others (Kiesling, et al., 2012). The diffusion models or Diffusion of Innovation (DOI) in marketing characterizes a phenomenon of communication of innovation in the social system via different communication channels such as mass media, interpersonal interactions, or other ways. Researchers majorly measure the diffusion counting sold units of a target product as a proxy. Since DOI can model various products' life cycles, many researchers, such as economists or statisticians, have been using diffusion models. Diffusion theory can also help stock managers compromising product availability and the cost structure for storage and handling. DOI supports executives in strategic planning to determine and control the inventory as part of the physical sales function (Aggarwal, et al., 2012). Therefore, SCM experts and engineers intended to improve the forecast quality of diffusions in this context.

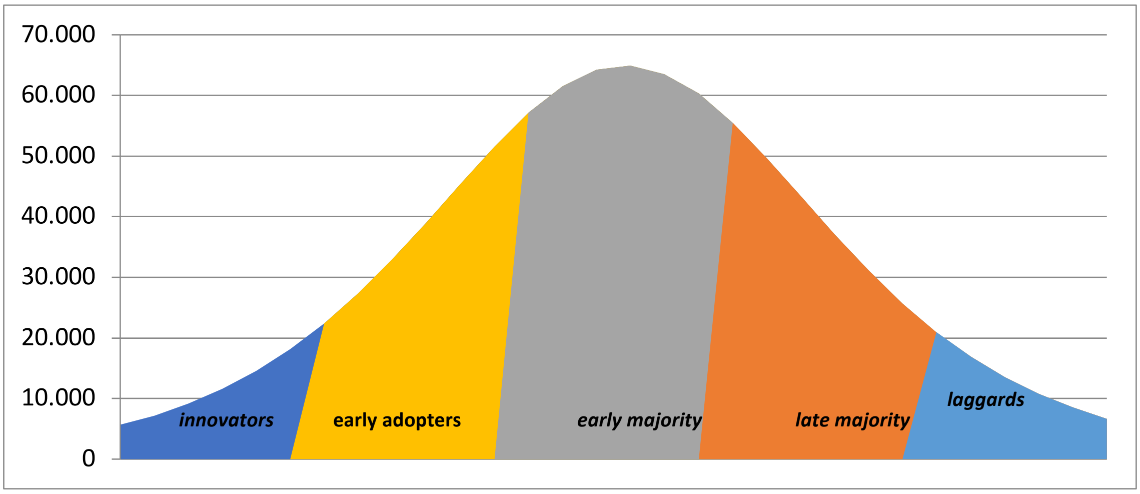


Figure 1. Bass Model- M: 1,000,000, p=0.005, q=0.25 colors represent: innovators, early adopters,

One of the most frequently used diffusion models in the literature is the Bass model (Bass, 1969). Although the model itself is straightforward, it has been applied and used to predict demand for 40 years since its conception. However, using the Bass model to evaluate the value of a specific product or technology has one significant shortfall; if there is no previous data on sales of new products, this task requires special skills to compensate for this lack of primary data. In this case, the typical approach is a qualitative approach to adjust future demand, making assumptions based on comparisons or similarities with other existing relevant products. The sensitivity due to selections of "those similar products" will notably influence the results. Therefore the characteristics of the products and similarity in the features will decide the diffusion model and life. Diffusion models have advantages over structural models when they are well designed. First, we can create diffusion models specifically designed to make strategic decisions before product launch and later during a product's lifecycle. We believe that it is accurate in many contexts. Second, since the focus is forecasting, diffusion models can be used correctly to predict demand for new launching products (the demand for MicroLed televisions, for instance).

In the NPD literature, we find many characteristics and distinct scale items (Garcia & Calantone, 2002) and many different possible features, such as industry, market, and customers' perspectives (O'Connor, 1998). We will follow the ideas proposed in (Lee, et al., 2014) and (Ganjeizadeh, et al., 2017). We think that advanced machine learning-based methods will improve predictive quality even if we do not have any sales history. We want to make a framework based on products' characteristics and run a parameter estimation of diffusion models for new products. Based on this framework, we like to make a universal demand forecast framework that can forecast industrial and electronics products. First, we intend to use one of the main qualitative methods to constitute an attribute database, including industry, market, technological, and product characteristics. We use both the Delphi method and the Analytic Hierarchy Process (AHP). These methods gather experts' (technicians, marketing professionals, and other specialists) opinions on new products for making market forecasts for them. Then, we define and constitute a database of attributes based on experts' views in circumstances, technological aspects, and the preference of general consumers where there is not past market data; then, we will use the same methods for the new products. Later on, the quantitative method comes into place. We use ML and DL algorithms to estimate the Bass model and compare them with traditional Looks-Like Analysis (Kahn, 2014). There are many attempts to structure all these procedures; however, most of them have some difficulties, and it comes to estimating demand curves in case there is no past information about the demand of the product, such as for new products. In fact, (Lee, et al., 2014) and (Ganjeizadeh, et al., 2017) combine many procedures.

2.3. Machine learning and ensemble methods

Large data sets and market intelligence have been big motivations for these applications, along with significant data availability. Mainly thanks to increasing the size of PoS data where companies record purchases, customer loyalty programs allow us to track individual consumers' behaviors, a posteriori to retain customers, and define new target groups (Einav & Levin, 2014). ML is one of the significant fields of artificial intelligence (AI), developing algorithms and technologies that enable computers to learn. In 1959, Arthur Samuel defined ML as "a field of research that develops algorithms that allow machines to learn from data and execute actions not explicitly specified in code." Since its inception, many researchers have developed theories and empirical exercises, which made breakthroughs, and ML have been preparing for a long time. However, at the time of inception, many found it is challenging to implement ML models in the real world since computing power and data-intensive. However, in the first two decades of the new century, ML models have become a serious competitor to classical and statistical models in the area of forecasting and optimization. Many other optimization methods fulfilled ML's tasks making the most of increased computing power and data.

Along with that revolutionizing computing power, the availability of big data and market intelligence have constituted big motivations for these applications, namely, significantly increasing the size of PoS data where companies record purchase histories. Customer loyalty programs allow us to track individual consumers' behavior, a posteriori to retain customers, and define new target groups. With the advent of online businesses, the user data at a massive scale to make more rational business decisions became necessary. Now more than many decades after its beginning and foundations, ML is becoming more focused on the future. Thanks to technological and social changes, many economists and marketing experts are also making the most ML methods, especially in retail and online business. Varian (Varian, 2014) divided data analysis in statistics and econometrics into four categories: 1) Prediction, 2) Description, 3) Estimation, and 4) Hypothesis Testing.

In our paper, we aim to use machine learning mainly for prediction making the most of ML's best strength, providing high-performance computer systems, which can provide useful predictions in severe computing conditions. We will focus on these regression tools as they are natural for many economic applications. Neural networks and machine learning are part of the so-called cognitive technologies that attempt to mimic human thinking and manipulate large amounts of knowledge, information, and performing objective analyses. Researches can apply virtually to any business process. Notably, as we already mentioned, these industrial products are prone to be highly sensitive to correct demand estimations; production prices tend to be high, and demands tend to be price-elastic. These facts suggest using methods based, for instance, on artificial neural networks (Tarallo, et al., 2019). ML and the computers' hardware/software have made significant progress in late years, and the applications are increasing in modeling demand for consumer products. On top of this, the best framework of demand forecast should also be accessible to adapt itself to the short time changes when another new development is substituting products. The post-launch update will enable the forecast models to change successive product generations' timing and structure with online-machine learning. ML-based technology will use all available product attributes and additional information, including product hierarchy, item descriptions, and external data, to find the best match between new and existing products.

The recent trend in applied econometrics is also very active in summarizing relationships in the data using ML methods. As we will see, ML uses many types of tools to synthesize meaningfully different types of nonlinear relationships in the data. We will focus on those similar tools as they are the most natural for industrial applications. ML has many benefits in forecasting the fast-changing demands of consumables (Croker, 2009). According to (Bryman, 2015), qualitative research's essential attributes are selecting appropriate methods and theories, identifying and analyzing different perspectives, reflecting on the study as part of the knowledge production process, and various approaches and techniques.

The literature shows that companies have used statistical techniques and tools to estimate their demand using historical sales series as their primary data source. However, according to (Kandananond, 2012), demand forecasts using machine learning have produced better quality results than traditional techniques. (Wu & Zheng,

2015) present sales forecasting models through machine learning and achieve higher accuracy than conventional statistical models for products with very volatile demand and very short life cycles. According to (Tsoumakas, 2019), machine learning techniques for predicting time series are more efficient and flexible than traditional statistical methods due to their higher processing power and ability to process additional variables. (Lu, 2014) Many factors, including sales, promotions, product features, and market indices, affect the accuracy of the supply chain's sales forecasts and efficiency. Therefore, the selection of variables is critical. (Qu, et al., 2017) build a database integrating both quantitative data and quantitative data in their machine learning algorithms. The main results are better sales forecasts and an inventory adjustment in luxury goods stores with seasonal characteristics and significant fluctuations in buying impulses.

The selection of data variables is crucial, but ML methods can even support time-series data without any trend for the estimates at disposal. (Guo, et al., 2013) suggests that a forecasting model based on multi-variable machine learning techniques can even make a better forecast than the conventional approach using historical data from previous orders. In the technology sector, (Lu & Shao, 2012) have used ML algorithms to provide more accurate sales forecasts for short lifecycle products, which will improve the supply chain process. (Lu & Zeigermann, 2014). (Lu, 2014) used a support vector machine (SVM) to improve the efficiency of highly interchangeable IT products subject to drastic changes in demand. (Lee, et al., 2014) developed a predictive model for selling innovative products in a study on 3D televisions whose technology had no sales history. They created a joint approach combining the qualitative methods and machine learning techniques, which resulted in higher accuracy than the other methods available. (Lu & Chang, 2014) have developed a hybrid sales forecasting model for IT products containing SVMs with greater efficiency and reliability than previous solutions. (Chen & Lu, 2017) confirm ML's benefits for technology businesses with short life cycle products by improving a computer retailer’s sales forecasting accuracy and inventory management.

The ensemble regression model combines multiple regression models to reduce a single regression model's bias and variance to predict performance better. There are mixtures of experts, depending on how the model is combined. In this process, the ensemble technique use bagging and bootstrap aggregating (Athey & Imbens, 2015) to increase the generalization performance of highly distributed complex models (e.g., artificial neural networks) and generates multiple learning data sets simultaneously. The first step is to create various training data simultaneously using reconstruction extraction for one training data set. In the second step, we will train highly complex regression models based on each generated training data. In the third step, we combine the trained regression models to produce one prediction result. The regression model created in the second stage, often overfit. However, in the third step, we can improve general performance by combining several regression models. Boosting (Schapire, 1999) is designed to increase the generalization performance of simple models with giant knitting. A mixture of experts (Masoudnia & Ebrahimpour, 2014) seeks to improve predictive performance by applying different regression models to the same training data or combining other regression models created by varying the same regression model's parameters. In general, ensemble models follow the procedure:

1. Select a combination of regression models (we use those models will expert mixing and the adjustable parameters for that model)
2. Perform model fit based on training data for selected model-parameter combinations
3. The results of the fitted model depend on the learning performance of the model

Deep Learning (DL) is an ML technique that uses deep neural network architectures to solve complex problems and a buzzword for its performance in many fields. In principle, DL is a type of Artificial Neural Networks (ANN) (Haykin, et al., 2009) that mimics the logical human brain, usually flat networks, consisting of an input, a hidden layer, and an output layer. However, DL networks differ from ordinary neural networks with more hidden layers or more depths (Goodfellow, et al., 2016). However, it turns out that a Deep Neural Network is more powerful and able to analyze and learn more complex characteristics and relationships than a traditional neural network. These systems can discover hidden structures in even unlabeled and unstructured data that make up the vast majority of the world's data. The DL approach can analyze the complex characteristics, relationships, and interactions between a problem's components using samples from a dataset and learn a model that we can use to predict demand (Lecun, et al., 2015).

Moreover, as computation power grows and the latest improvements to the Graphical Processing Unit (GPU) and parallel architectures have enabled deep neural networks, computing power is required. DL uses successive layers of neurons; each layer extracts more complex characteristics from previous layers' output. DL allows computers to learn from experience without supports from a human operator to specify knowledge, understanding the world in terms of a hierarchy of concepts with deep layers built on top of each other. DL has become a trendy research topic among researchers and provides impressive results for image processing, computer vision, natural language processing, bioinformatics, and many other areas (Bengio, 2012).

Tensor Flow is a software library mainly for numerical calculation of mathematical expressions using data flow diagrams (Singh & Manure, 2020). Google created it and made it available as an open-source version and adapted it for machine learning. Today, Tensorflow is one of the most widely used methods for developing many DL solutions. TensorFlow, combining with Keras, is one of the best libraries to implement deep learning. With open-source availability, more and more people in artificial intelligence (AI) and ML academics and communities make the most of TensorFlow and Keras. They helped users implement standard deep learning algorithms and supported users to implement customized and differentiated algorithms for various research purposes. Scikit-learn is a Python module integrating many machine learning algorithms. This library is a subset of the SciPy (Scientific Python) library group, which is a set of libraries created for scientific computing and especially for data analysis (Nelli & Nelli, 2015) and the SciPy group defined these libraries as scikits, hence the first part of the name of this library.

3. The set-up proposal (database, estimation, and analysis)

3.1. The Database

In the first stage, "Information gathering," we first performed a literature study and established our paper's primary objectives. In terms of the Bass parameters and product database selections, there are three main approaches- 1) direct estimations using all the methods mentioned below, 2) a meta-analysis based on authoritative sources, and majorly quoted estimation results from reliable sources. Finally, 3) expert questionnaires asking for seven parameters needed. The following diagram shows our full set-up proposal.

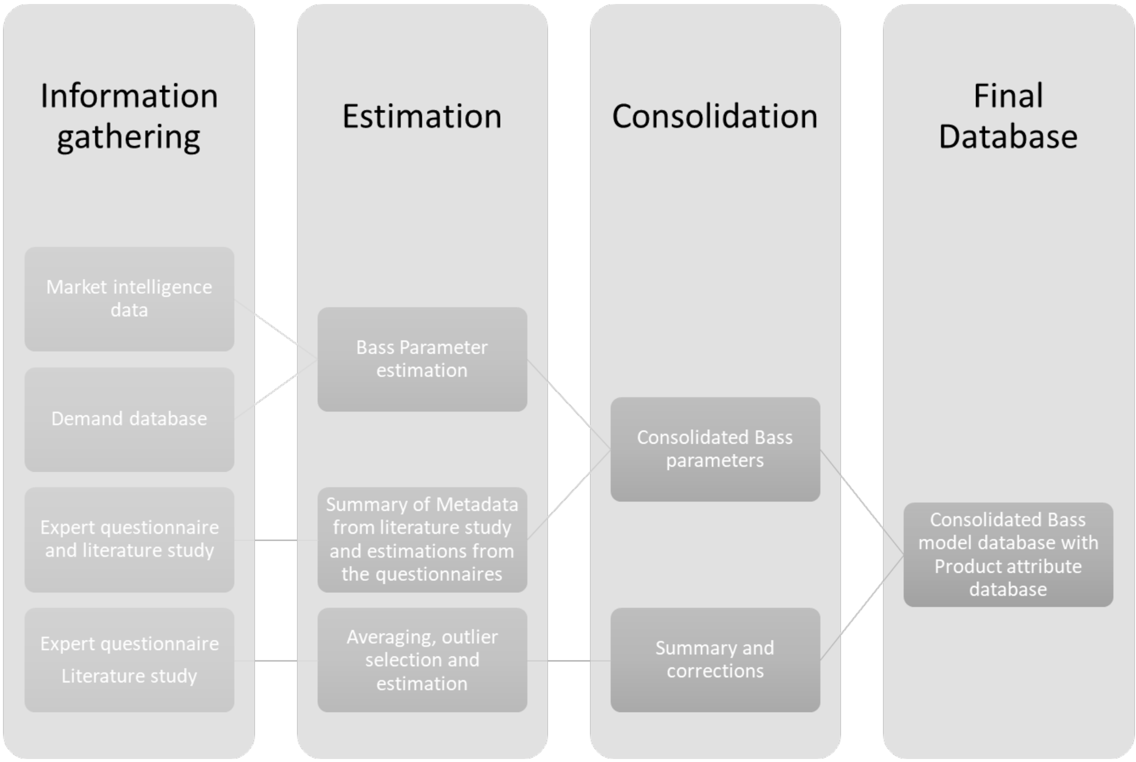


Figure 2. The Set-up flow

3.1.1. Demand database and integrated market intelligence data

Our primary method of getting the Bass parameters in our paper is direct estimation from historical data. This method follows the basic setup from the proposed framework (Lee, et al., 2014). After thorough considerations, the demand database gathered from various sources was combined into Product Group, Year, Month, Country, and Sales Units. Additionally, we also collected demand data from many websites, papers, and reports such as Consumer Electronics Association(CEA), European G2k market intelligent, Demand data from Korean products through various associations in Korea, Demand data from Bassbasement.org, and many more such as OCED stats and World Bank database.

To measure the prediction accuracy of the regression model, we assessed each model using two performance indicators: Ordinary Least Squares (OLS) (Bass, 1969) and Negative Mean Absolute Error (NMAE; Lee, et al., 2014). One evaluates OLS estimation using the goodness of fit, i.e., the ratio of the variance described by the regression equation among the dependent variable's deviations, equal to the power of the correlation coefficient between the actual and predicted values. The first OLS method uses the parameter estimation method of regression analysis (Bass, 1969). OLS method is a method of converting coefficients to quadratic equations and estimating them through regression analysis. Although OLS is the most used method, it cannot evaluate discrete data in continuous models.

$$\sum_{i=1}^{n}(y_i-\bar{y})^2=\sum_{i=1}^{n}(\hat{y}_i-\bar{y})^2+\sum_{i=1}^{n}(y_i-\hat{y})^2 \tag{2}$$

$$TSS=SSR+SSE \tag{3}$$

$$R^2=\frac{SSR}{TSS}=1-\frac{SSE}{STT} \tag{4}$$

Negative Mean Absolute Error (NMAE) – an average of the absolute error of the actual and predicted values

$$\text{NMAE} = -\frac{1}{n}\sum_{i=1}^{n}|y_i - y'| \qquad \textbf{\textit{(5)}}$$

In our paper, as in (Lee et al., 2014), we found few differences between OLS and MAE. However, we also found that OLS sometimes produced unreliable prediction during our experiments. NMAE can be an excellent measurement for the Bass parameter estimation (Scitovski & Meler, 2002). As discussed in chapter 2, we use NMAE as the loss function to measure errors in the presented analysis. We use negative MAE (NMAE) to implement sklearn, which solves minimization problems to handle them both in the same way. The second NMAE method uses the likelihood estimation function (Schmittlein & Mahajan, 1982). NMAE is just inverted MSE in losses (errors); the higher (closer to 0), the better. The NMAE technique proposed to overcome this limitation is that NMAE allows us to evaluate parameters' statistical significance. To make the most of cross_validate using the utilities present in scikit, we have to use 'neg_mean_squared_error' since sklearn solves a minimization problem. With all the background mentioned, we use Python Scikit-learn entirely, directly importing modules from sklearn for the implementation like below. The function evaluate_model gets any trained model to return the cross-validation score, measured by negative man absolute error (NMAE). However, in the machine learning perspective, the ideal NMSE is not 0 because this would mean the model would correctly predict all the training data, but that will return higher prediction errors. Therefore, we need to balance overfitting (very low MSE for training data) and underfit (very high MSE for test/validation/unseen data).

3.1.2. Meta-analysis

Our main aim of doing metadata analysis is to give some more reliability base parameters with consistency. In the literature study accurately, we also run a meta-analysis in the sense of (Sultan, et al., 1996), which develops initial parameter estimates by performing a meta-analysis from 15 papers to make the complementary basis the Bass parameter database. Many of the results from other studies with similar characteristics can explain the intent–behavior relationship (Morwitz, et al., 2007). This process mainly refers to authoritative sources and majorly quoted estimation results from reliable sources(Massiani & Gohs, 2015). The first step in a meta-analysis involves selecting the studies to include in the database and publishes tables. Either we find the base parameters directly, or we calculate them using proxies and statistical adjustments. Out of 17 studies, from 5 sources, we got mainly direct estimations for p,q, and m parameters. We applied an m-weighted average for p and q after performing minimum data cleansing- namely, omitting outliers. From the rest 12 sources, we could calculate p and q or m was not 1:1 comparable and used related proxies to estimate the Bass parameters. Here is how we did first; we plot them and eliminate outliers. Then we calculate them using proxies such as cumulative sales F* and net sales (n*) at the highest point, Net adopters at first period n1, and the degree of stagnation (r) as we will present in the next section. To yield robust estimation results, we follow the procedure (Kim, et al., 2013) by removing outliers, verifying conformability, and reducing errors. After selecting all parameters p and q, we applied an unweighted average. We present those sources and aggregation methods in Table 1.

Table 1. Sources of meta-analysis and aggregation method

Source	Aggregation Method	Year
Bass's Basement Research Institute.	Outlier elimination Weighted average based on m	Various
CBEMA IT Data Book 1960-2000		
Electrical Merchandising		
Merchandising & Dealerscope		
The Information Technology Industry Data Book		
(Kohli et al., 1999)		1999

(Lilien et al., 2000),	Outlier elimination, as in (Kim, Hong, and Koo, 2013) Unweighted Average	2000
(Isaacson and Frank, 2001)		2001
(Talukdar et al., 2002)		2002
(Tellis et al., 2003)		2003
(Van Den Bulte and Stremersch, 2004)		2004
(Stremersch and Tellis, 2004),		2004
(Jiang et al., 2006)		2006
(Meade and Islam, 2006),		2006
(Chandrasekaran and Tellis, 2007)		2007
(Lee et al., 2014b)		2014
(Moutinho and Sokele, 2017)		2017

3.1.3. Expert surveys

(Mahajan, et al., 1986) and (Lawrence, et al., 2009) show one can use maximum sales level for parameters and the sum of the coefficients of external and internal influences, respectively. Many studies refer to expert opinions based on algebraic derivation (Gupta, et al., 1999). Simple diffusion models are more likely to make the most of this approach (Morwitz, et al., 2007). Algebraic estimates based on expert surveys show a reasonable and efficient conversion of knowledge and experience into model parameters. Moreover, well designed and summarized, we can quickly and accurately convert rounds of surveys into the Bass model parameters. Experts' comprehension of mathematical models appears to differ because of the diversity of their backgrounds and professional experience.

In our paper, we follow the structure from (Lawrence & Lawton, 1981) (Lawrence, et al., 2009) and (Kim, et al., 2013). The main advantage of using this method is that we can also use expert judgments about product attributes and categories. We tried to find questions to overcome the limitations of the previous work. (Kim, et al., 2013) suggests that net adopters at first period n1, the highest time t*, and the accumulated users at t*, N*, are precious from the information content. (Lawrence & Lawton, 1981) uses the sum of innovative and imitative parameters and market potential in the survey. Therefore, in principle, we ask for these five parameters in our questionnaire, using the Delphi method to achieve this by allowing experts to make their forecasts anonymously and privately. At the same time, we review their forecasts when we share still anonymous and unmapped arguments and statistical summaries of the group's current view each round with the experts (Rowe & Wright, 1999). We carefully design three simple and straightforward rounds of questionnaires for the experts to obtain reliable estimates of the Bass estimates. After getting the desired parameters, in addition to their interpretation value, these can easily be transformed with simple algebraic equations (Lawrence, et al., 2009) to make them correspond to the Bass parameters:

$$p = \frac{n^*(m)}{(m-N^*)^2} \qquad \textbf{\textit{(6)}}$$

$$q = \frac{n^*(m-2N^*)}{(m-N^*)^2} \qquad \textbf{\textit{(7)}}$$

$$t^* = \frac{(m-N^*)}{2n^*} ln\left[\frac{m}{m-2N^*}\right] \qquad \textbf{\textit{(8)}}$$

3.1.4. Product attributes

As discussed before, we aim to use product attributes as an alternative to Look-like analysis. We perform the subjective evaluation by combining experts' intuitive knowledge with information about the diffusion properties of existing similar products based on an expert evaluation based on more specific information such as coefficients of external and internal influences (Lawrence & Lawton 1981). Despite its merits, the subjective approach has one of the biggest but innate weaknesses since it lacks a systematic procedure to convert survey results into reliable dissemination parameters (Kim, et al., 2013) than look-like approaches. (Kim, et al., 2013) proposes a systematic method to convert survey results into good results, and (Lee, et al., 2014) apply it for the Bass model. In the spirit of (Lee, et al., 2014), we built a product demand database that includes product name, year, serial number, number of consumers, the cumulative number of consumers. As we briefly mentioned, we use the expert panel for parameter estimation. However, the 3 round expert questionnaire's essential part was making the best subset of each category's product attributes and values. It is necessary to derive the variables affecting the product life cycle to estimate the Bass model parameters m, p, and q based on their attributes (Machuca, et al., 2014). We have finally selected twenty-three product attribute variables in five categories from previous literature studies and expert advice (Song, et al., 2015). The main categorizations of the product attributes are similar to (Lee, et al., 2014) and based on the relevant panels' information. We measure those attribute variables for the estimated parameters (a summary table is in the Appendix). We summarize those characteristics below.

Table 2. Major characteristics for the final Bass database

	Variable	Definition	Details
Industry characteristics: Those are the macroscopic features of the industry itself to which the product belongs	**(a~c)**	(Industry classification): the industry type according to the official classification system in the UN Stat(unstats.un.org).	**ISIC Rev.4 26**: ELECTRONIC, COMPUTER, AND OPTICAL PRODUCTS ISIC **ISIC Rev.4 27, 35** ELECTRICAL EQUIPMENT, ELECTRICITY, GAS, STEAM, AND AIR CONDITIONING SUPPLY **ISIC Rev.4 28** MACHINERY AND EQUIPMENT N.E.C. **Others**
	(d~f)	(Competition industry): the industry competition level (mainly based on the number of firms in the industry and the level of market share).	This paper classifies the competition intensity into three types: monopoly (1), oligopoly+(2~4), and perfect competition.
	(g)	(Need and accessibility of substitution industry): The level of need for supplements, the degree of demand for other products to supplement the product's consumption and utilization.	The higher the need for supplements, the more significant other products' proliferation on the product's life cycle.
	(h)	(Level of existing complementary industry): The degree of substitution, indicating the presence of other products that may replace the product.	The higher the level of replacement, the shorter the life cycle or the slower the spread.
Market characteristics: Those are the	**(i)**	(Average Selling Price): Consumers' purchases of products occur when the cost of the work is lower than utility,	In general, the lower the price, the faster the spread, and the higher the likelihood of reaching peak demand in a shorter period

general characteristics of the market itself, and available indicators of the product's distribution	**(j)**	(Level of potential demand): The number of buyers means the size of potential buyers who will purchase the product:	In this paper, the more buyers, the more active the word of mouth spread.
	(k)	(Horizontal/Vertical integration of logistics channels): The number of distribution channels means the number of channels through which a consumer can purchase a product.	The more various types of distribution channels and the larger the number, the faster they spread.
	(l)	(Possibility of suppliers): The number of potential suppliers is the number of companies supplying the product.	The more suppliers, the more likely the consumer is familiar with external influences such as advertising.
Technological characteristics: Those are the characteristics of the technology utilized or embodied in the product	**(m~n)**	(Innovation factor): It indicates whether the novelty of the technology of the type of change is radical or incremental.	If the innovation is progressive, it is not familiar to consumers, and the diffusion is slow. More likely to buy new products more actively.
	(o)	(Current change speed in the related field): The rate of technological change represents the rate of development and progress of associated technologies.	If a technological change occurs rapidly, it is unlikely that consumers will catch up with their level, making it difficult to achieve rapid spread or relatively short life cycles.
	(p)	(Accessibility): Imitation and Entry technology indicates the ease of reproduction and duplication of the technology.	If the copy is smooth, there is a high possibility that many companies supply the same product, and there is a possibility that similar or alternative products may emerge and erode the market. level, The potential of imitation of the
Product characteristics: Those are the attributes of a product at the micro-level	**(q)**	(Type of product): Product type: whether the product is essential or luxury goods	If it is critical material, the work's life cycle is long, and it is likely to continue to spread. However, luxury goods often do not cover well.
	(r)	(Difficulties and Needs for learning): The need for education: the level of time and cost of knowledge required for the consumer to use the product	The higher the need for understanding, the more difficult it is to use the work, and the less likely it is to spread.
	(s)	(Variety of use and application) Functional diversity: the types of additional functions in addition to the essential services of the product.	The more diverse the features, the higher is the utility, and the better is the spread.
Usage characteristics: Those are the	**(u)**	(Frequency of usage): The rate of the way how the consumers use. It also measures how often we use the product.	If the rate of use is high, it is likely to have the characteristics of essential goods or to be repurchased frequently

behavioral aspects of consumers who use the product	**(v)**	(Average duration of usage): The term of use: the life cycle of using the product from purchase to disposal.	The longer the period of use, the lower the frequency of repurchase. Furthermore, the less likely to use, and the slower the spread.
	(w)	(Frequency of repurchase) The need for repetitive purchases: maybe it can be needed more than 1 in a household or depends on the failure rate due to the product's short service life.	The higher the demand for repeated purchases, the longer the life cycle, and the more likely it is to reproduce.

3.1.5. Consolidating the Bass database with product attribute survey results

In the next step, mainly based on all features defined in (Lee, et al., 2014), we designed a short questionnaire. We use the Delphi method to develop the questionnaire and ask for some basis of the Bass parameters. The Delphi method is an effective method of using the subjective approach and majorly used in new product forecasts (Kahn, 2010). (Kim, et al., 2013) uses an increased number of survey items then filter the survey results using compliance rules, outliers, and consistency to improve the reliability of a subjective expert survey-based approach to pre-launch forecasting. The proposed method reduces the error caused by wrong answers or expert estimates and provides more robust estimation results than previous work. Our rounds of the questionnaire consist of questions about the Bass Parameters and Industry Characteristics, Market Characteristics, Technological Characteristics, and Product Characteristics. In the next level, we invited industry experts and asked them and summarized and then analyzed the first-round questionnaire results asking additional questions if needed. These experts included engineers and marketing managers from significant manufacturers and distributors and wholesalers. With all available data checked from various sources and results from questionnaires, we established a product demand database for products that collected demand data. We also use those characteristics for the prediction of similar products using the Analytic Hierarchy Process (AHP; Tseng & Lin, 2015) and expert surveys and conjoint analysis (Lee et al., 2006) to obtain estimates of the diffusion of a specific new product introduction (Cestre & Darmon, 1998).

The next step is cleansing the demand database and estimating three parameters m, p, and q of the Bass model. The combined database comprises many products, including mobile phones, Vacuum cleaner, Refrigerator, Washing machine, Audio devices, Televisions, etc. Below are some essential products' demand curves. Using the combined product demand database from various sources, we used Python's 'leastsq' and 'curve_fit' modules from 'scipy.optimize' for the parameter estimations. Those modules allow us to solve nonlinear least-squares problems with bounds on the variables using the Levenberg–Marquardt algorithm (Moré, 1978). It runs the Levenberg-Marquardt algorithm formulated as a trust-region type algorithm. Then, we perform feasibility checks and merge them with databases gathered from other literature. Based on a literature study and solid empirical research, we will follow the proposed framework based on (Lee, et al., 2014) and (Ganjeizadeh, et al., 2017). The parameters of 174 products were estimated- the descriptive statistics are below, and we present all of m, p, q values in the Appendix. The corresponding results and Python code are also in the Appendix. Based on the data collected from sources mentioned before, we selected 174 products (149 unique products regardless of geographical differences) and 36 product characteristics

Table 3. Major statistics of the final Bass database

	m	p	q
Average	15,692,454	0.0235	0.3167
Std	58,420,276	0.0384	0.2235

Max	389,745,519	0.2821	1.2066
Min	4,605	0.0000	0.0000

3.2. Estimation

In the next step, the employed learning algorithms are optimized based on the training data set. As we saw in section 3.1, we have collected a sufficient real-world demand database, which we let randomly divide and shuffle into training and test data sets. We use the most common method for evaluating a regression model: cross-validation. However, the total number of products used in this project is tiny (174 product groups). If the training data is insufficient, there is a risk that the accuracy of the regression model fit will deteriorate. Then an accurate evaluation is needed. Leave-one-out leaves only one product for assessment and builds a regression model using all remaining products. The best models will then be identified based on the test data set, then mixed by ensemble methods.

3.2.1. MLR models with L1 and L2 regularization techniques

Multiple Linear Regression (MLR) predicts the relationship between multiple independent variables (inputs) and dependent variables (targets) as a linear model. MLR is quite a standard method in economics; therefore, we skip the detailed explanation. To find the parameter estimates $(\hat{\beta}_j's)$ we use Ordinary Least Squares (OLS), i.e., find the $(\hat{\beta}_j's)$ to minimize the residual sum of squares (RSS), i.e., minimizing the loss function:

$$L_0 = Error(y, \hat{y}) = \sum_{i=1}^{n}(\hat{y}_i - y_i)^2 = \sum_{i=1}^{n}\left(\sum_{j=1}^{k+3} x_{ij}\,\beta_j - y_i\right)^2 \qquad \textbf{\textit{(9)}}$$

If we define alternative loss functions:

$$L_1 = Error(y, \hat{y}) = \sum_{i=1}^{n}(\hat{y}_i - y_i)^2 = \sum_{i=1}^{n}\left(\sum_{j=1}^{k+3} x_{ij}\,\beta_j - y_i\right)^2 + \lambda \sum_{j}^{k+3}\left|\beta_j\right| \qquad \textbf{\textit{(10)}}$$

$$L_2 = Error(y, \hat{y}) = \sum_{i=1}^{n}(\hat{y}_i - y_i)^2 = \sum_{i=1}^{n}\left(\sum_{j=1}^{k+3} x_{ij}\,\beta_j - y_i\right)^2 + \lambda \sum_{j}^{k+3} \beta_j^2 \qquad \textbf{\textit{(11)}}$$

An MLR model with an L1 regularization technique constitutes a Lasso Regression and a Ridge Regression with an L2 regularization method. The critical difference between these two is the penalty term. First, as we can see, either L_1 or L_2 loss function, if λ =0, the equation above reduces to L_0. Therefore if we have low λ on the features, the model will resemble the linear regression model. If we have L_1-regularization, it is a modulus. The derivative of the function is essential here. Of course, the derivative is vital since the gradient descent mainly moves in the derivative direction. L_1-regularization realizes this by selecting the most critical factors that most affect the result. This reason prevents over-fitting from Lasso regression, facilitating our feature selection.

In L_2, as we can see, Lasso regression has a squared beta coefficient as the penalty term to the loss function. The additional term is a quadratic function for L_2-regularization. Therefore, it prevents the model from retraining by prohibiting disproportionately large weights. The penalty term λ regularizes the coefficients such that if the coefficients take large values, it penalizes the optimization function. It is useful to imagine a model with a one-dimensional weighting factor. 'Sklearn.LassoCV' and 'Sklearn.RidgeCV computes the cross-validation score as a function of α (the strength of the regularization for L_1 and L_2). This process optimizes meta-parameters and enables both Lasso and Ridge regularizations to make the most of the methods.

The parameters of 174 products were estimated- the descriptive statistics are below, and we present all of m, p, q values in the Appendix. The predictive performance measured by NMSE for estimating the Bass Model parameters p and q are summarized below.

Table 4. Predictive performance of different MLR models methods

	MLR		Lasso CV		Ridge CV	
	p	**q**	**p**	**q**	**p**	**q**
Average	0.023	0.317	0.023	0.117	0.023	0.317
Std	0.021	0.090	0.018	0.010	0.020	0.081
Max	0.088	0.575	0.067	0.317	0.083	0.556
Min	0.000	0.103	0.000	0.000	0.000	0.128
NMSE	**Mean**	**std.**	**Mean**	**std.**	**Mean**	**std.**
	-0.096	0.018	-0.093	0.015	-0.095	0.021

Both L_1 and L_2 regularizations show better performances in NMSE in comparison with MLR, and Lasso (L_1) offers slightly better results than L_2. The predictive performance of those three regression models for estimating the Bass Model parameters p and q in NMSE is summarized below in a box-and-whisker plot presenting predictions results. MLR has a smaller range of Q1 and Q3 in terms of the median. However, it loses some of its predictive power due to some outliers.

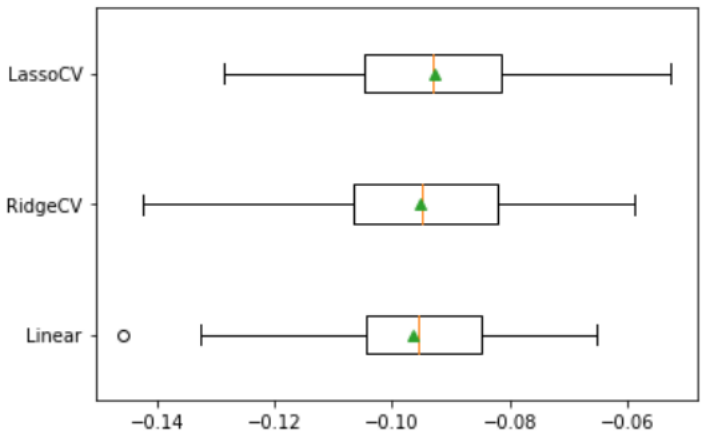


Figure 3. Box-and-whisker plot presenting predictions in terms of NMSE

Lasso CV regression shows the best prediction accuracy for both p and q parameters and indicates a stable range of errors. The main reason for the linear regression analysis may be because the number of independent variables is high (23). So L_1 regulation helps with feature selection, and cross-validation processes minimize over-fitting issues. In general, we can see that we can apply rules and cross-validations directly, improving MLR's limitations.

3.2.2. Machine Learning algorithms

Classification and Regression Tree (CART)

Decision Trees are an essential type of algorithm for predictive modeling machine learning used in situations where the results' interpretation is critical. The reason is because of its high explanatory power compared to other data mining techniques. In a decision tree, each node is input variables (x), and the leaf nodes of the tree are output variables (y). Classification and regression tree is a representative decision tree technique that constructs a regression model using recursive branching and pruning. Recursive pruning uses the rule of "yes/no" is applied based on the value where information acquisition or impurity reduction is most significant for a particular attribute. We can make predictions by going through the branches of the tree until arriving at a leaf node. Classification and Regression Trees have the following advantages:

1) Easy to understand the for humans meaning of results to interpret intuitive results since it performs predictions using If-Then type rules
2) Trees can learn and predict fast, and they take less time on data preprocessing
3) They generally do not require any special preparation, such as data normalization and missing value processing
4) It can handle numerical and categorical variables simultaneously, therefore often accurate for a broad range of problems
5) Decision trees have high variance and can be combined with other algorithms when used in an ensemble

With all the background mentioned, we use Python Scikit-learn entirely, directly importing modules from sklearn for the implementation like in the appendix. Scikit-Learn performs splitting to separate the data into smaller groups. It continuously branches the given training data to build a full-tree where we use Mean Absolute Error (MAE) to minimize information loss.

K-Nearest Neighbor (k-NN) Regression

The KNN algorithm is straightforward and very effective. Searching the entire learning set for the most similar K-instances (the neighboring ones) makes predictions for a new data point. It summarizes the output variable (in KNNR, the mean output). KNN regression selects k objects that most closely resemble the item's specific properties (product) to be predicted and then select the dependent variables (the Bass model). Here, estimating the values of p or q using the weighted sum using similarity between subjects, as in the target variable value expression of the new item, KNN regression selects k objects that most closely resemble the object with properties (product) to be predicted and then select the dependent variables (p and q of the Bass Model). The similarity between the two products X and Y with d attribute values are measured using the Minkowski distance function, as shown in equation (16):

$$\text{distance}(X, \mathrm{Y}) = \left(\sum_{i}^{n} \left|\mathrm{x_i} - \mathrm{x_j}\right|^{p}\right)^{\frac{1}{p}} \qquad \textit{(12)}$$

The determination of the distance between the data is an essential part of this algorithm. The most straightforward technique when p = 2 is the commonly used Euclidean distance to calculate the differences between each x directly. Researchers widely use k-neighbor regression, a variety of practical classification, and regression modeling because of the following advantages: 1) There is no training phase; it needs to calculate when the data makes predictions. Therefore, we can quickly update our training instances over time to keep predictions accuracy. 2) Since we do not need to make any assumptions about the distribution, it is possible to estimate various relationships (linear and nonlinear). 3) When we obtain a large enough number of training data, the performance is excellent, comparable to other modern machine learning and data mining algorithms.

However, KNN regression requires much memory to store all of the data, and the predictive performance may vary depending on how the optimal number of neighbors (k value). Moreover, if there are many x variables (high dimension), the distance can also break down into substantial sizes that can be computationally expensive and might negatively affect the algorithm's performance. Therefore, we think it is essential to find an optimal k and only use those input variables using cross-validation and locally linear reconstruction techniques. In turn, we get optimal k and the most relevant variables for the prediction.

Support Vector Regression (SVR)

Support Vector Regression (SVR) is one of the most popular machine learning algorithms since the early 2000s after artificial neural networks. It uses the structural risk minimization technique during the learning process to reduce the risk of overfitting. It performs high-level projections onto a hyperplane that splits the input variable space using kernel tricks to estimate nonlinear complex curves in low-dimensional input spaces. In SVR, we select a hyperplane to best separate the point's area by their class (either class 0 or class 1) in the input variable. By doing so, SVR minimizes the most significant margin (the distance between the hyperplane and the closest data points). We call those points the Support Vectors, and we use them to define the hyperplane and in the construction of the regressor. In practice, to find the values for the coefficients that maximize the margin, we need to use an optimization algorithm. SVR fits the regression equation $\hat{y} = w^t x + b$ with the constraints of including training instances as many as possible in the ε -tube can be expressed by an optimization equation like below

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) - \sum_{i=1}^{l}\alpha_i(\varepsilon + \xi_i - y_i + w^T x + b)$$
$$- \sum_{i=1}^{l}\alpha_i^*(\varepsilon + \xi_i^* + y_i - w^T x - b) - \sum_{i=1}^{l}(\eta_i\xi_i^* + \eta_i\xi_i^*)$$

$$\text{s.t. } \alpha_i, \alpha_i^*, \xi, \xi_i^* \geq 0 \qquad \textbf{\textit{(13)}}$$

w is the coefficient of the regression equation, ζ and ξ * are penalties for the data outside of ε-tube, and the constant C (> 0) is the difference between the flatness of the function and the error outside of ε-tube. i.e., trade-off control ratio. We construct a Lagrangian function without constraints to solve the equation above, and the optimal solution conditions that perform partial derivatives on the Lagrangian derivative variable are:

$$\frac{\partial \mathrm{E}}{\partial \mathrm{w}} = w - \sum_{i=1}^{l}(\alpha_i^* - \alpha_i)x_i = 0$$
$$\frac{\partial \mathrm{E}}{\partial \mathrm{b}} = \sum_{i=1}^{l}(\alpha_i^* - \alpha_i) = 0$$
$$\frac{\partial \mathrm{E}}{\partial_{\xi_i^{(*)}}} = C - \alpha_i^{(*)} - {}_{\eta_i}{}^{(*)} = 0 \qquad \textbf{\textit{(14)}}$$

By taking the derivatives of the primary variables, we obtain the optimal conditions for the Lagrangian; in turn, we get Wolfe's dual problem by replacing the terms above the primary problem:

$$\max -\tfrac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_i - \alpha_i^*)x_i^T x_j - \epsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) + \sum_{j=1}^{l} y_i(\alpha_i - \alpha_i^*)$$

$$\text{s.t. } \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0, \alpha_i, \alpha_i^* \in [0, C] \qquad \textbf{\textit{(15)}}$$

The solutions for α and α* represent the optimal solution. SVR shows the excellent predictive performance when equipped with sufficient data, and appropriate algorithm parameters are selected. However, there are relatively many algorithm parameters, and the deviation of the result according to the parameter value is significant. Therefore, the setting's appropriateness must be sufficiently verified through cross-validation and then applied to the prediction model.

The 174 products' parameters were estimated- the descriptive statistics are below, and we present all of m, p, q values in the Appendix. We show the predictive performance of three non-linear algorithms, KNN (Best out of non-linear algorithms), CART, and SVM, in Table 5, where we also report their predictive performance measured by NMSE.

Table 5. Predictive performance of different SVR methods

	KNN		CART		SVM	
	p	**q**	**p**	**q**	**p**	**q**
Average	0.024	0.331	0.023	0.317	0.018	0.068
Std	0.026	0.109	0.038	0.223	0.014	0.177
Max	0.106	0.577	0.282	1.207	0.048	0.609
Min	0.000	0.152	0.000	0.000	0.000	0.000
NMSE	**Mean**	**std.**	**Mean**	**std.**	**Mean**	**std.**
	-0.097	0.019	-0.122	0.027	-0.136	0.050

KNN regression shows the best prediction accuracy for both p and q parameters. SVM offers the worst performance and sometimes fails to converge. The main reason for SVM's failure, maybe because the number of products used for learning is insufficient (174). CART shows better performance than SVM, but it delivers worse performance than any other MLR model with L_1/L_2 regulations. Both CART and KNN offer better performance in NMSE than the MLR method, and KNN shows even better prediction accuracy for both p and q parameters compared to L_1/L_2 regularization. The predictive performance of those three regression models for estimating the Bass model parameters p and q in NMSE is summarized below. CART shows better understanding than SVM and MLR, but it delivers worse performance than any other MLR model.

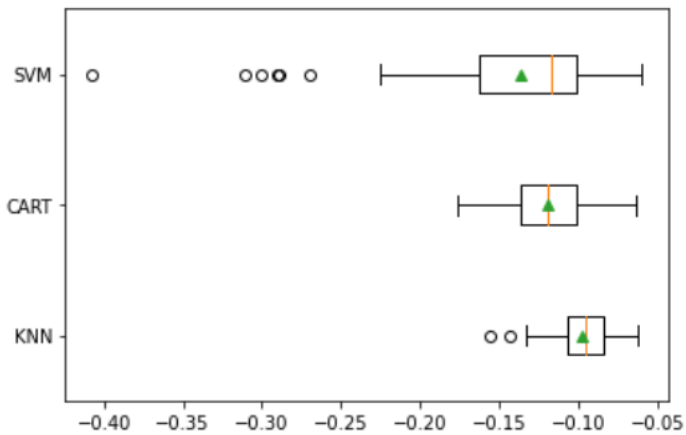


Figure 4. Box-and-whisker plot presenting predictions in terms of NMSE

3.2.3 Ensembles of ML algorithms

Bootstrap Aggregation

Random Forests is an Ensemble method for classification and regression. It creates many Decision Trees at the time of training, and the class is the output that represents the prediction mean (for regression) of individual trees. Random decision forests correct the habit of decision trees to fit our training set. Random Forest is an optimization of this approach, in which even though it creates decision trees. However, instead of selecting optimal division points, it makes suboptimal divisions by introducing randomness. Therefore, the models developed for each data sample are different than usual but are still accurate in their unique and different ways. The combination of our predictions leads to a better estimate of the underlying actual output value.

Boosting

Boosting is an ensemble technique trying to create a robust classifier from several weak regressors. In general, the process works as follows: we make a model from the training data. Then, we create a second model that tries to correct the errors of the first one. We add additional models until the models predict the training set correctly or reach a maximum number of predetermined models. One of the most well-known boosting, “Adaptive Boosting” (AdaBoost), aims to convert a set of weak regressors into a strong one. It uses short decision trees. After creating the first tree, it measures and uses the tree's performance in each training instance to weigh how much attention must pay to the next tree made in each training instance. It gives more weight to complex training data ('weak learners') to predict it carries less weight while easily predictable examples. This way, it combines the output of weak learners’ algorithms into a weighted sum representing the boosted regressor's final output. Then, it creates the model one at a time and updates the weights in the training instances that affect the next tree's learning in the sequence. It weighs the performance of each tree according to the accuracy of the training data. Gradient Boosting Regressors (GBR) is a kind of inductively generated tree set model. Every training phase trains a new tree against the loss function's negative gradient, similar to residual error. Extreme Gradient Boosting Regressors (XGBR, XGBoost) is an implementation of gradient boosting machines.

The 174 products' parameters were estimated- the descriptive statistics are in Table 6, and we present more information in the Appendix. We summarize the predictive performance of three boosting ensemble algorithms, AdaBoost, GBR, xgboost (the best of our boosting algorithms), and the best bagging ensemble model, measured by NMSE, for estimating the Bass Model parameters p and q Table 6 and Figure 5. In terms of performance measured by NMSE, Random Forest shows the best performance beating the best-boosting ensemble model, xgboost.

Table 6. Predictive performance of different boosting methods

	AdaBoost		GBR		Random Forest		xgboost	
	p	**q**	**p**	**q**	**p**	**q**	**p**	**q**
Average	0.034	0.368	0.023	0.317	0.023	0.324	0.023	0.317
Std	0.028	0.124	0.034	0.166	0.028	0.156	0.032	0.151
Max	0.282	0.740	0.261	1.061	0.212	0.903	0.232	0.995
Min	0.010	0.192	0.000	0.060	0.001	0.087	0.000	0.077

NMSE	Mean	std.	Mean	std.	Mean	std.	Mean	std.
	-0.102	0.019	-0.097	0.021	-0.092	0.021	-0.095	0.022

Random Forest and xgboost show better performance than Multiple regression methods and KNN (best single ML method) in NMSE. Random forest regression shows the best prediction accuracy for both p and q parameters, although the prediction span shows some high dispersion. The predictive performance of those three regression models for estimating the Bass Model parameters p and q in terms of NMSE is summarized below. Other Boosting algorithms, except for xgboost, have marginally lower accuracy than any other MLR

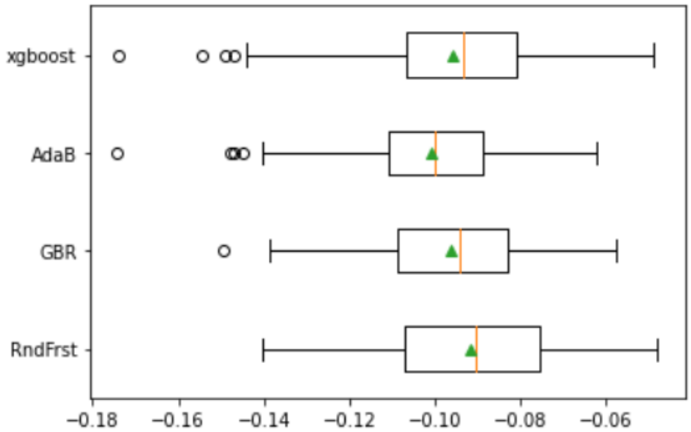


Figure 5. Box-and-whisker plot presenting predictions in terms of NMSE

or other ML methods. The biggest reason for Boosting algorithms' failure may consist of the number of products used for learning is insufficient (174). GBR shows better performance than AdaBoost and SVM, but it offers worse performance than any other MLR model with L_1/L_2 regulations.

3.2.4. Deep Learning: TensorFlow and Keras

TensorFlow 2.0, released in October 2019, has redesigned the framework based on user feedback in many ways to improve work and performance. Kera's design is easy to use, modular, easy to expand, and work with Python. The API was "developed for humans, not machines" and follows "best practices for reducing cognitive stress." Neural layers, cost functions, optimizers, initialization schemas, activation functions, and regularization schemes are separate modules that we can combine to create new models. We can add new modules quite easily as new classes and functions. Models are defined in Python code, not in separate model configuration files. We use the Python Keras library entirely directly

The 174 products' parameters were estimated- the descriptive statistics are below, and we present all of m, p, q values in the appendix. We will compare four models here. The predictive performance of Lasso SV (Best Linear Model), KNN(Best ML model), Random Forest (Best Ensemble model), and Deep Learning measured by NMSE for estimating the Bass model parameters p and q are summarized below.

Table 7. Estimates of p and q parameters and their performance with different methods

	Lasso CV		KNN		Random Forest		Deep Learning	
	p	**q**	**p**	**q**	**p**	**q**	**p**	**q**
Average	0.023	0.117	0.024	0.331	0.023	0.324	0.026	0.290

Std	0.018	0.010	0.026	0.109	0.028	0.156	0.024	0.096
Max	0.067	0.317	0.106	0.577	0.212	0.903	0.096	0.679
Min	0.000	0.000	0.000	0.152	0.001	0.087	0.000	0.139
NMSE	**Mean**	**std.**	**Mean**	**std.**	**Mean**	**std.**	**Mean**	**std.**
	-0.093	0.015	-0.097	0.019	-0.092	0.021	-0.089	0.020

In terms of performance measured by NMSE, Deep Learning shows the best performance beating the best ensemble model, Random Forest, by 0.03. We also summarize the predictive performance of those six regression models for estimating the Bass Model parameters p and q in Figure 6.

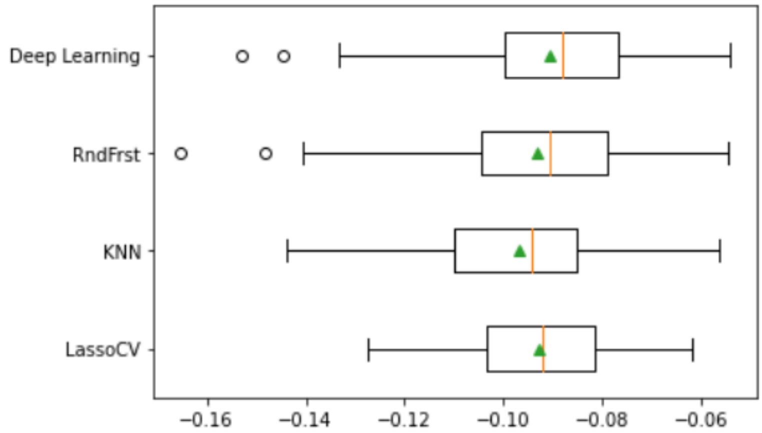


Figure 6. Box-and-whisker plot presenting predictions in terms of NMSE

Let us compare all the best models with the best Deep Learning model. The Deep Learning model outperforms any kind of linear, non-linear, and Ensembles in terms of NMSE, even compared with the best ensemble model, Random Forest, even though it shows some outliers. Nevertheless, as we will show in the next section, Deep learning shows somewhat different and inconsistent predictions than MLR, with similar projections compared with KNN. However, Random Forest offers quite identical patterns of forecasts when compared with Lass and MLR. L_1 regulation shows consistent predictions and shows different predictions, majorly overestimating p and q compared with other methods up to specific points, then underestimating from particular values and over.

3.3. <u>Comparison of different methods</u>

To summarize the individual estimations and visualize some high performing methods, we show below the p, q projections of LassoCV, KNN, Random Forest, which are the best single linear, machine learning, and best Ensemble model, respectively. We also show the Deep Learning results compared to the predicted target values by the MLR method. Here, we set MLR results as baseline targets, and we will compare four models with MLR: the best linear and non-linear single model (i.e., Lasso CV and KNN), and the best ensemble model (i.e., Random Forest) and Deep Learning. Of the all possible combinations of regression algorithms and ensemble models, Deep Learning showed the best performance in terms of MLE, meaning the lowest statistical information loss given all product characteristics. Nevertheless, it does not always lead to the best-predicted parameters. This process will not give us measurements to evaluate the models' performance but will provide us with feelings about their behaviors comparing to ordinary OLS regressions.

The next two figures below show the relationship between the MLR estimation values for p and q. They also present the ones with the best algorithms in terms of R^2. It shows that the prediction is very accurate regardless of the range of p and q. In the case of MLR analysis, with increasing p and q, there is a tendency to overestimate the distribution of points on the baseline except for the Lasso CV approach. In contrast, the rest of the regression models tend to underestimate the distribution of points below the baseline. Figure 7 compares the "p prediction performances" of MLR with the best single and ensemble models. The picture depicts the estimated Bass model parameters (target estimated value by MLR, x-axis) and prediction outcomes (y-axis predictions by best algorithms). The straight line in those figures represents the ideal cases where predicted results (ŷ) with each algorithm are equal to their baseline targets. Thus, the closer the points approach the line, the better is the model for prediction purposes. In this respect, the Lasso CV method for p is the most different from MLR in terms of R^2. Additionally, its prediction coverage is much narrower than that of the actual targets. Namely, its predicted p values are generally located within 0 and 0.07, although their target values keep staying in the range of 0 to 0.3. Random Forest shows the highest performance in terms of goodness of fit R^2 =0.92, and it shows the most significant similarity to MLR. In Random Forest, KNN, and Deep Learning, with increasing p, there is a tendency to overestimate the distribution of points on the baseline except for the Lasso CV. In contrast, the rest of the regression models tend to underestimate the distribution of points below the baseline.

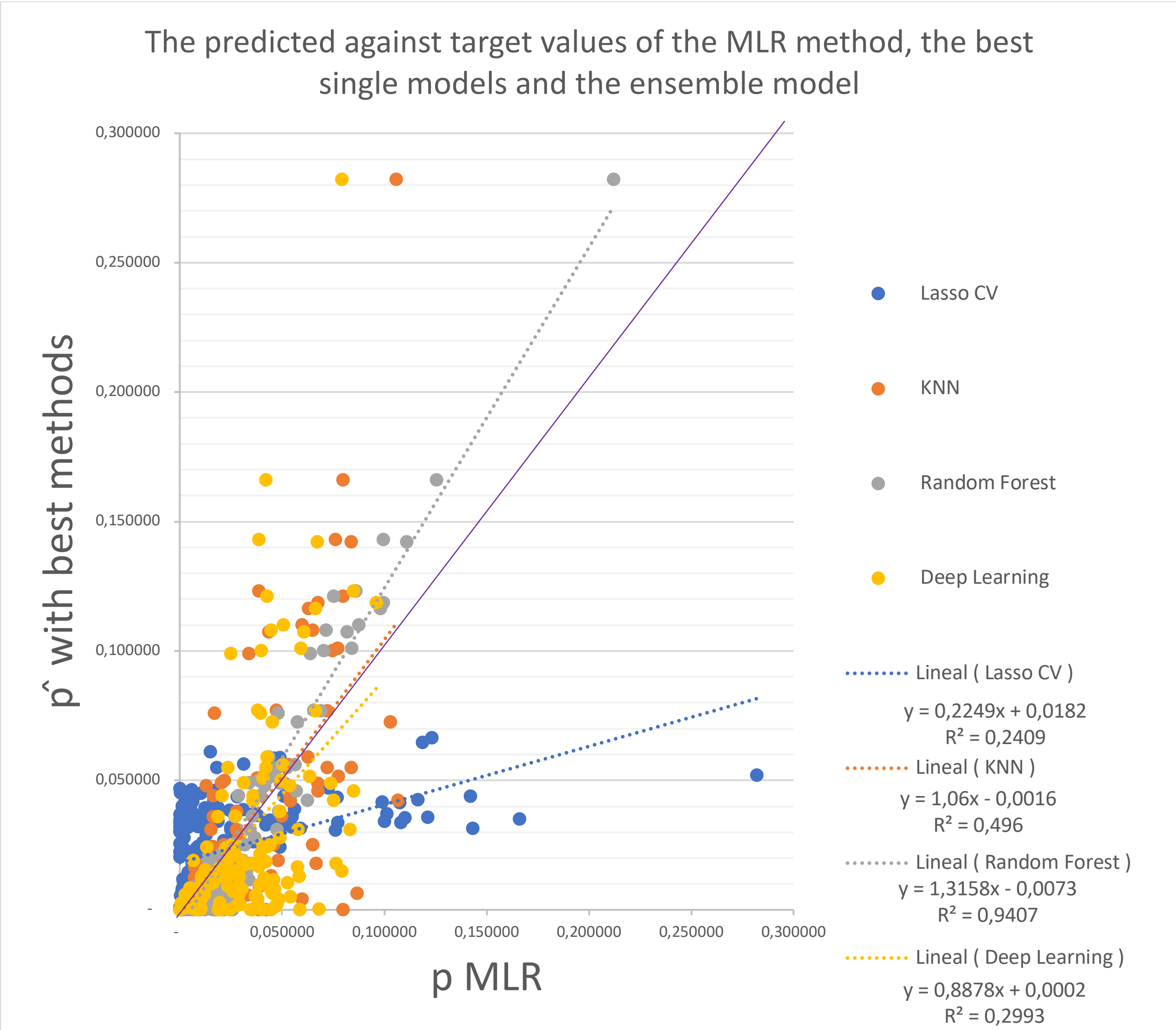


Figure 7. Predicted p against target values of the MLR method, the best single models, and the ensemble model

Figure 8 compares the “q prediction performance” of MLR with the best single and ensemble. The picture depicts the estimated Bass model parameters (target estimated value by MLR, x-axis) and prediction outcomes (y-axis predictions by best algorithms). The Lasso CV method for q is the most different from MLR in terms of R^2 = 0.158 and of all models since we see the most sparsely dispersed distribution. 0~0.3 range it overestimates and 0.3~ it underestimates comparing to MLR. Besides, its prediction coverage is much narrower than MLR baseline targets. Its predicted q values are generally located within 0.2 and 0.5, although their target values range from 0 to 1.2. In terms of goodness of fit measured by R^2 Random Forest shows the highest one R^2 =0.91 and it shows the most significant similarity to MLR and KNN and Deep Learning show quite similar R^2 and similar results. In the case of Random Forest, KNN, and Deep Learning, with increasing q, there is a tendency to overestimate the distribution of points on the baseline.

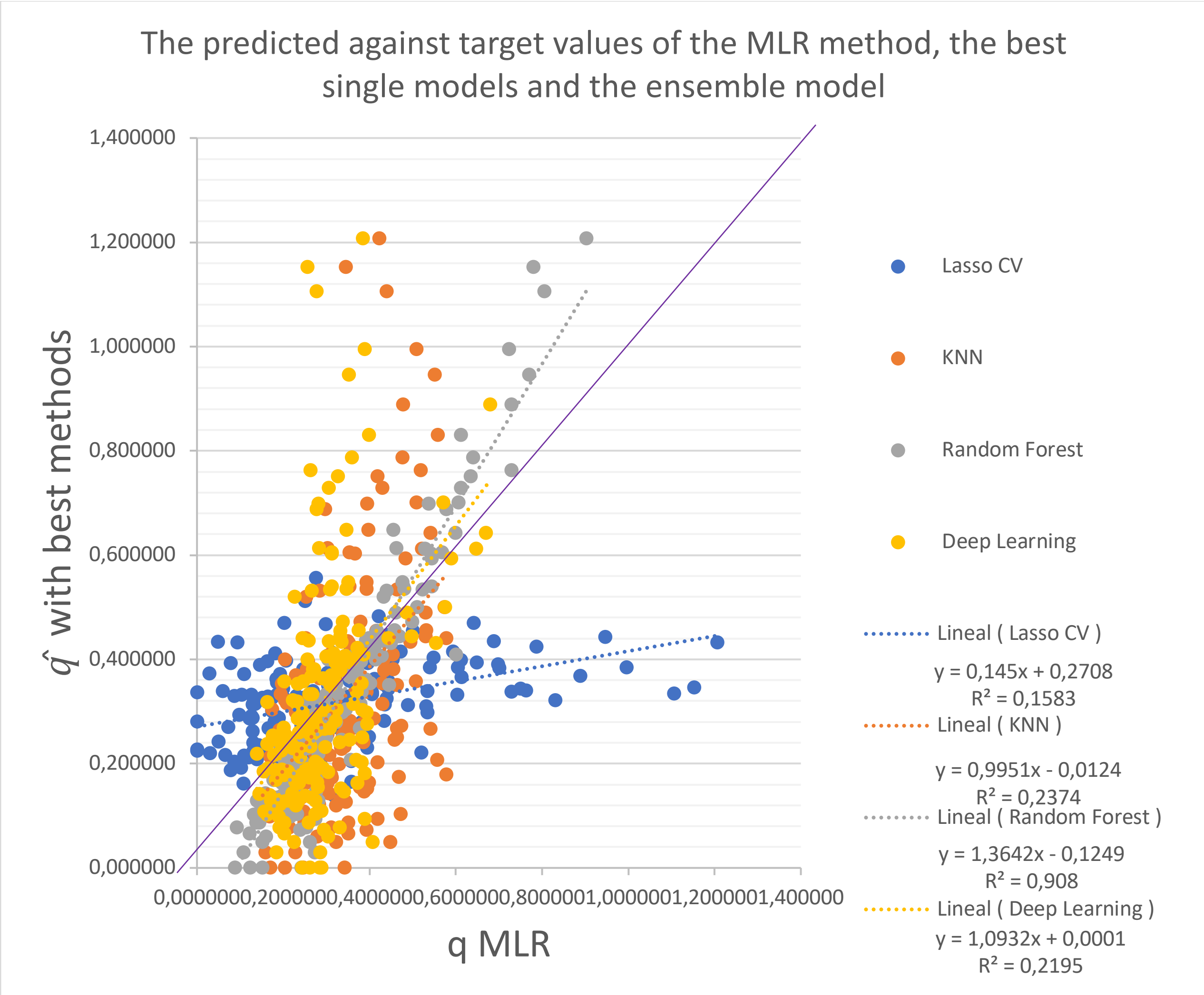


Figure 8. predicted Q against target values of the MLR method, the best single models, and the ensemble model

By combining Lasso CV, which tends to overestimate, and Deep Learning or Random Forest, which tends to underestimate the parameters comparing to MLE, we think to make an accurate estimate of the entire range and confirm that most of the points are above the baseline. It seems as though the randomness and we can solve this biased coverage of these predicted outcomes using the Random Forest Ensemble. As for KNN and Deep Learning, we observe two other issues. First, KNN tends to over-estimate the estimates beyond a certain extent (p= 0.02 and q =0.05). Moreover, Deep Learning tends to overestimate p and under-estimate q parameters beyond a specific scope. Constructing an ensemble model resulted in the prediction errors decreasing significantly for both p and q; almost 90% of the analogical method's MAE disappeared in both cases. Compared with the best single model (i.e., Lasso CV), the ensemble Random Forest model still provided a surprising improvement; over 75% of prediction errors were reduced for both p and q regardless of the performance measures.

In sum, the Deep Learning method seems to show the most outstanding results in terms of NMSE, even though it indicates somewhat different results from other methods. In theory, Random Forest and KNN both base on the empirical risk minimization scheme showing in general reliable results. As we can observe, both Random Forest and KNN offer similar estimation patterns and low R2 in estimating p. As for q, MLR shows a similar forecast for the same product group with Random Forest. In contrast to Random Forest and KNN, however, Deep Learning shows a unique forecast in estimating p and q. In general, the LassoCV with L1 regularization has lower slopes for p and q, comparing to all other models. In the case of p, MLR, and q, L1 regularization shows excellent performance. Its NMSE -0.089 is the biggest among all algorithms, and it is more than 15.1% of the average of the estimates and 3.37% more than the second-best algorithm, Random Forest, and 7.87% better than the MLR method. (see below) NMSE of SVM shown almost 52.81% more than those of the Deep Learning.

Table 8. Summary comparison of main methods

Average	NMSE	NMSE ratio Deep Learning	Remarks
MLR	-0.096	107.87%	Stable results and benchmark with other methods
Lasso CV	-0.093	104.49%	Excellent performance estimating q and lower slopes
SVM	-0.136	152.81%	SVM shows terrible performances and sometimes fails to converge
Random Forest	-0.092	103.37%	Second-best algorithm and shows similar forecasting patterns to MLR
GBR	-0.097	108.99%	Best of three boosting algorithms
Deep Learning	-0.089	100.00%	The best algorithm showing unique forecasting patterns
Average 10 Methods	-0.1025	115.17%	

4. Empirical Application

In this section, we forecast the demand for MicroLED TV in five European markets, making the most of the Bass model database with characteristics that we proposed in section 3. Using this data, we examine all p, q parameters using all the algorithms. It is crucial to identify market diffusion dynamics since MicroLED technology is one of the most beloved products after OLED televisions. Starting surveyed consumers' purchase intentions in the European market to estimate the potential market size, we use household data from 2010~2019 and Flat TV sales data in Europe as a proxy for the possible market size. Our primary focus is to show how one can empirically apply our database with trained models to estimate the parameters of the two types of communication effects: namely p, innovation, and q, imitation comparing to the conventional look-like approach.

4.1. MicroLED

During US 2018~2020 Consumer Electronics Show (CES), various manufacturers showcased MircoLED TVs. Moreover, it is a known fact that even other manufacturers without TV production, such as Apple and Oculus, acquired MicroLED companies due to the importance. MicroLED is a new technology similar to OLED since it is self-emitting screen technology, allowing making screens even brighter and more efficient. There are currently no microLED screens in mass production, but many manufacturers already test and boast MicroLED technology. For example, “45-inch digital signage using microLED technology” from LG, "Crystal LED" from Sony, and the "the Wall" from Samsung are products using this technology.

Experts believe that MicroLED has the potential to challenge OLED in the future. The reason is not only due to the advantages mentioned above, but it does not have burn-in effects of OLED since it does not use organic material in the pixel but an inorganic material such as GaN (gallium nitride). MicroLEDs are extremely small, typically 1/10 the width of a human hair, which allows them to be deposited as a matrix of pixels on a substrate to make a screen (Samsung, 2018). It will be extremely competitive in the future, as many manufacturers (such as Sony, Samsung, LG, Apple) are interested in MicroLED. While Korean manufacturers such as LG and Samsung are already preparing for mass-production and increasing the investments, Epistar and Leyard Opto-Electronics intend to build a $142 million micro-LED Konka announces a $365 million Micro-LED R&D center. MicroLED is might ultimately replace the current LCD and OLED market in the future. Therefore, predicting the life cycle and demand for MicroLED can provide valuable information for developing related technologies, establishing production plans, and developing marketing strategies. MicroLED is extremely difficult to manufacture on a large scale and requires much investment, implying that there is the possibility of forecasting the distribution of TV demand in advance. With drastic substitution patterns and increasing market uncertainties, and this significant amount of investment, the capability to predict TV demand distribution in advance provides valuable decision supports. Forecasts are, therefore, important for planning the delivery of new products, logistics, and investments. Accurate predictions support the implementation of marketing strategies and guidelines, while incorrect predictions lead to wasted resources.

4.2. Forecast: Analogy or Applying Looks-Like Analysis

Analogy (Lee, et al., 2014) or Looks-Like Analysis (Ganjeizadeh, et al., 2017) calculates p and q from previous analog product sales. The model has three parameters: p, which represents the influence of innovators and, therefore, is known as the innovation coefficient, q which means the impact of previous users (imitators) and, therefore, is known as the imitation coefficient, and m, the final number of consumers. The prediction problem can then be reduced to the problem of determining p, q, and m. Here, we use the Analogy (Look-like analysis) method, first for p and q. That is, select p and q by searching for similar new products that companies previously introduced and that we already have historical demand data to estimate these parameters. The problem for p and q is choosing the best analogy from a large number of products (152) previously introduced. To obtain information on methods to adjust established intentions to more accurately reflect actual behavior, we used the database that we created from meta-analysis and questionnaire in sub-section 3.2. This database derives methods to predict the actual purchases of new products based on stated expert opinions. We use the Analytic Hierarchy Process (AHP) to get the final models for MicroLED.

Our first step in determining a base forecast is to identify similar products (analog products) with previous sales data in our database. To do this, we search other literature and ask experts for products and our database that are already available on the market, compare their properties, check their similarity, and determine correlations. Many of the results from other studies with similar characteristics can explain much of the variation in the intent–behavior relationship (Morwitz, et al., 2007). Five devices, Digital TV Sets & Monitors, Plasma DTV, Color TV, Projection TV, and LTV Flat, were found and compared with MicroLED. The following table compares factors, including industrial market technology products for each of the five devices. To calculate p and q, we run a pairwise comparison, and we can see them in the table below. Using these correlations we calculate MicroLED’s p = 0.0087 and q: 0.3957.

Table 9. Estimation of p and q by Analogy

Product	p	q	Industry	Market	Technology	Product	Use	Corr.
Weight			**0.125**	**0.250**	**0.275**	**0.250**	**0.100**	**1.000**
Digital TV Sets & Monitors	0.00100	0.50030	0.2	0.1	0.2	0.2	0.2	**0.180**
Plasma DTV	0.00130	0.59310	0.1	0.2	0.1	0.1	0.1	**0.120**
Color TV	0.00010	0.64852	0.1	0.2	0.1	0.2	0.2	**0.160**
Projection TV	0.00512	0.20626	0.1	0.1	0.1	0.1	0.1	**0.100**
LTV Flat	0.01789	0.25021	0.5	0.4	0.5	0.4	0.4	**0.440**

MLR, a regression line for the cumulative sales and sales per year of the MicroLED, was calculated. Our regression results are shown in the following subsection and compared to the machine learning estimate. MicroLED might ultimately replace the current LCD and OLED market in the future. Therefore, predicting the life cycle and demand for MicroLED can provide valuable information for developing related technologies, establishing production plans, and developing marketing strategies. First, we assess the five significant variable values of the MicroLED TV attributes. We see the measured characteristics of MicroLED TV values below. The best simple regression model (MLR) and the best overall model (MLR and GPR) were used to predict the MicroLED TV parameters. The potential market size m was then estimated to predict annual demand. As an illustration, this section indicates the future direction for MicroLED TV in the German market. Previous studies have examined consumer intentions to estimate the potential size of the market. However, in this paper, we use the total number of households in Germany (41.3M) to measure possible market size. This case example aims to illustrate how to use predictive models to estimate the parameters of the two types of effects, innovation and communication. We forecast the demand for MicroLED television in Germany for 15 years (from 2021 to 2036) by combining the total number of German households in 2018 with the two predicted parameters p, q. Figures below (a) and (b) show the annual and cumulative demand trends derived from the specified model. Comparing forecasts with actual sales data from the early years can confirm the validity of forecast models.

Table 10. Product attributes of MicroLED

	Attributes	Values	#	Attributes	Values
a	Industry classification :G	1	n	Innovation factor: I	1
b	Industry classification :E	0	o	Innovation factor: R	0
c	Industry classification: M	0	p	Current change speed in the related field	5
d	Competition industry :MO	0	q	Accessibility(Imitation and Entry-level)	2
e	Competition industry :OL	1	r	Type of product: M	0
f	Competition industry :PE	0	s	Type of product: N	1
g	Need and accessibility of substitution industry	3	t	Difficulties, Needs for learning	2
h	Level of existing complementary goods	3	u	Variety of use and application	2
j	Average Selling Price	4	v	Frequency of usage	3
k	Level of potential demand	3	w	The average duration of usage	3

l	Horizontal/vertical integration of logistics channels	4	x	Frequency of repurchase	3
m	Possibility of suppliers	3			

We will then look at the Bass model's parameters predicted by the four highest predictive models and compare four models with Look-like analysis. The MLR indicates p and q as 0.0558 and 0.5168, respectively; other estimated parameters using the best linear and non-linear single models and the best ensemble models are in the table below. The table below shows our modeling results, in which the NMSE method will determine all the Bass model parameters (p and q).

Table 11. Bass model based on product properties of MicroLED

Machine Learning algorithm type	Algorithm	Estimated parameters for MicroLED		Coefficient	t-statistic
		p	*q*	*NMSE*	*std*
Linear	MLR	0.0558	0.5168	-0.096	0.018
	Lasso CV	0.0568	0.3167	-0.093	0.015
	Ridge CV	0.0554	0.5012	-0.095	0.021
Non-Linear	KNN	0.0673	0.2287	-0.097	0.019
	CART	0.0080	0.4210	-0.122	0.027
	SVM	0.0599	0.0026	-0.136	0.05
Ensembles	RndFrst	0.0423	0.3498	-0.092	0.021
	GBR	0.0890	0.3412	-0.097	0.021
	AdaB	0.0564	0.4309	-0.102	0.019
	xgboost	0.0798	0.3398	-0.095	0.022
Deep Learning		0.0875	0.4239	-0.089	0.02

Of the all possible combinations of regression algorithms and ensemble models, Deep Learning showed the best performance in terms of MLE, meaning the lowest statistical information loss given all product characteristics. Nevertheless, it does not always lead to being the best to predict parameters. To investigate how m varies with the moderation variables, they reduced m to the different products' variables. This model starts with the underlying assumption that the conditional probability that a new product is purchased by potential consumers (the percentage of the population of prospective users that have not purchased them yet) at a given moment is a function that increases linearly from the number from previous users. The demand expectation varies by source; many experts make forecasts based on analog. One forecast microLED shipments to reach over 450 million panels by 2027. According to "Display Daily," the total demand is expected to reach 329 Millon by 2026.

On the other hand, according to IHS, 160 million per year will be the global demand by 2024 ("Display-Technik: Micro-LED wird 2024 reif sein - so IHS," n.d.). Finally, n-tech research says that the MicroLED will experience speedy growth, by 2028, with 170 million lighting units shipped. On the contrary, another source predicts MicroLEDs, which will begin to sell in earnest in 2021, account for only 0.4 % of global TV production in 2026(Mertens, 2019). The remaining columns of the table contain the calculated explanatory parameters that a forecaster can easily interpret: –t - characteristic duration of the product/service, the time. The multiple linear regression analysis has predicted that values are significant in both the innovation coefficient p and the imitation coefficient q. Based on the estimation of two parameter values, we performed domestic MicroLED demand and life cycle forecasts for the next 20 years as of 2021. The potential market size, m, does not affect the life cycle, but the demand value itself. Below we see an exemplary good forecast for Germany. We also show MicroLED estimates for France, Italy, and Spain in the appendix. As for Germany, to forecast demand by year, we applied a possible market size of 41.3 million domestic households (as of 2020) from OECD stat. The results of the life cycle prediction based on the multiple linear regression analysis parameters are as follows. As we can see, the start and peak times in the Deep Learning model come slightly before in time than those from the ensemble model, such as Random Forest and Look-like analysis. It always shows the latest peak time.

Table 12. MicroLED Lifecycle Key Points-Multiple Linear Regression Criteria

	Year					
Life cycle	Looks-Like	Random Forest	Lasso Regression	KNN	XgBoost	Deep Learning
(T_1)	2028	2024	2024	2024	2023	2023
(T^*)	2031	2026	2026	2027	2025	2025
(T_2)	2033	2029	2029	2030	2028	2027

We can get essential points in the product life cycle (PLC), such as the start (T1) and the peak (T *), which in turn forecasts the PLC of MicroLED. Based on Looks-Like analysis, as we see mid-2028 as takeoff, early 2031 as peak, and late 2033 as accumulation. The best ensemble model (Random Forest) predicts those points a bit earlier since it predicts mid-2024 as takeoff, early 2026 as peak, and late 2029 as accumulation. Deep Learning predicts the most initial MicroLED life cycle the leap season when demand starts to increase in earnest is 2.4 years, meaning in mid-2024. The current top market is five years and is expected in 2025 when the maximum order is about 8.9 million TVs. The saturation period was seven years and was predicted later in 2027.

We will then look at the Bass model's parameters predicted by the four highest predictive models and compare four models with Look-like analysis. The best linear and non-linear single model (i.e., Lasso CV and KNN), and the best ensemble model (i.e., Random Forest) and Deep Learning are in the table below.

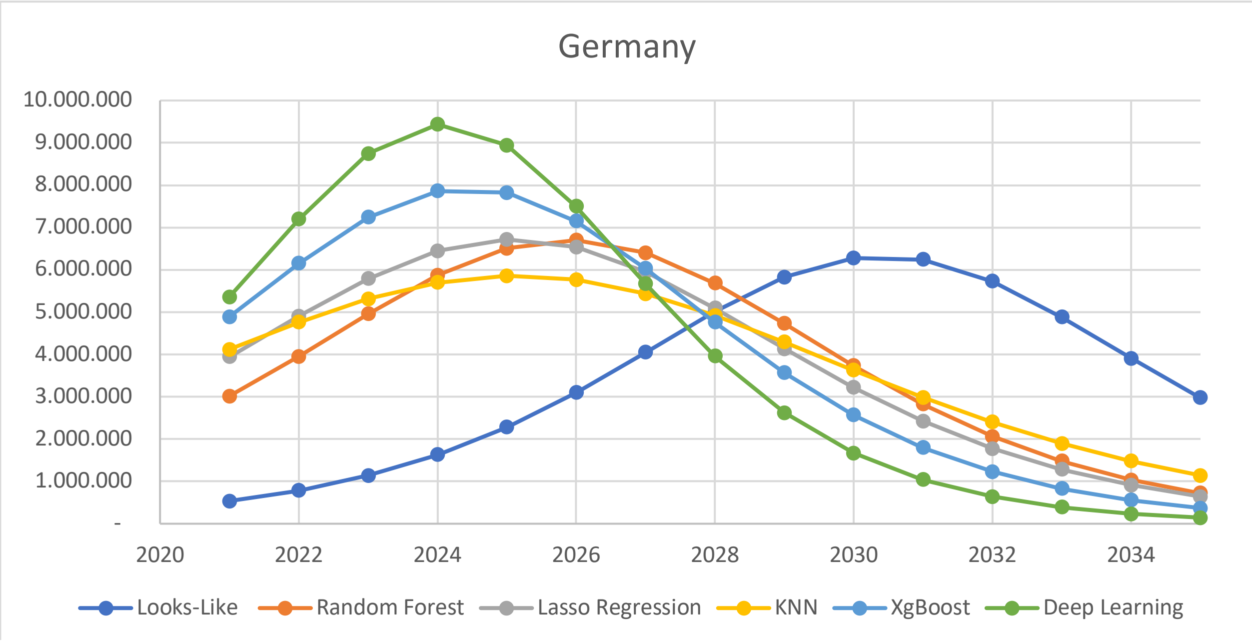


Figure 9 Life-cycle summary of MicroLED Annual Demand Trend in Germany

Table 13. German MicroLED Demand Forecast by Year-Multiple Linear Regression Criteria (Unit: Persons)

Year	Looks-Like	Random Forest	Lasso Regression	KNN	XgBoost	Deep Learning
2021	534,650	3,013,417	3,942,731	4,119,013	4,886,079	5,355,203
2022	784,179	3,952,520	4,900,314	4,762,676	6,152,706	7,193,385
2023	1,138,434	4,954,633	5,789,964	5,314,646	7,237,179	8,748,815
2024	1,628,335	5,869,769	6,445,847	5,700,222	7,858,782	9,435,622
2025	2,280,124	6,506,088	6,717,428	5,859,605	7,825,387	8,941,895
2026	3,099,478	6,700,186	6,535,473	5,766,255	7,147,884	7,495,087
2027	4,047,156	6,397,412	5,946,812	5,435,846	6,033,260	5,665,249
2028	5,015,003	5,682,039	5,090,546	4,920,918	4,763,094	3,958,286
2029	5,825,070	4,731,393	4,134,648	4,294,201	3,566,334	2,616,926
2030	6,277,494	3,732,689	3,217,355	3,629,026	2,566,100	1,667,753
2031	6,240,929	2,821,295	2,421,067	2,984,779	1,794,138	1,038,192
2032	5,726,508	2,064,139	1,776,310	2,400,653	1,229,423	636,888
2033	4,881,198	1,474,491	1,279,193	1,896,411	830,903	387,206
2034	3,906,695	1,035,380	908,885	1,476,919	556,343	234,122
2035	2,972,567	718,317	639,618	1,137,536	370,183	141,093
2036	2,176,174	494,185	447,096	868,685	245,290	84,859
2037	1,548,654	338,028	311,049	659,058	162,085	50,977
2038	1,080,047	230,303	215,689	497,546	106,909	30,601
2039	742,684	156,485	149,224	374,211	70,431	18,361
2040	505,764	106,133	103,077	280,658	46,362	11,014
2041	342,150	71,893	71,123	210,050	30,503	6,606
2042	230,431	48,659	49,038	156,956	20,062	3,962
2043	154,722	32,914	33,793	117,145	13,192	2,376
2044	103,678	22,256	23,279	87,354	8,673	1,425
2045	69,379	15,045	16,033	65,097	5,701	854

2046	46,385	10,168	11,040	48,487	3,748	512
2047	30,993	6,872	7,601	36,102	2,464	307
2048	20,700	4,643	5,233	26,873	1,619	184
2049	13,821	3,138	3,602	19,999	1,064	110
2050	9,227	2,120	2,480	14,881	700	66

5. Results and discussion

We can summarize the result of this empirical application:

1. We find Deep Learning and Random Forest regression to be the best single prediction model in NMSE. The correlation coefficients between the MLR prediction values and the forecasted values with other algorithms show that Random Forest shows are excellent performance maintaining NMSE low

2. Followed by Deep Learning, KNN Regression results show higher prediction accuracy than other single prediction models

3. Regression algorithms with higher complexity, such as SVM, Lasso CV, and Ridge CV, as well as other Boosting algorithms, result in lower prediction accuracy than those with more moderate complexity due to the limited number of training data; we can improve their predictive power by increasing the size of the product database with more product attributes

4. The ensembles combining single models with Random Forest show the most accurate model

5. The correlation coefficients between the MLR prediction values and the predicted values by Deep Learning innovation (p) and the ratio of imitation (q) are 0.9872 and 0.9853, respectively, which are approximately 10% higher than those of the MLR

All in all, the experimental results can be summarized as follows. First, the product attributes configured herein are valid, as they lead the regression algorithms to get accurate prediction results. Second, statistical and machine learning-based regression algorithms result in a higher predictive power than the conventional analogical model. Among the regression algorithms, the best single prediction model is Lasso CV, not only because its prediction error rate is the lowest one, but also because it has the most evenly distributed residual errors. Lastly, the Random Forest ensemble model significantly enhanced the prediction accuracy of the single regression algorithms. Besides, Deep Learning improved the NMSE errors even further than Random Forest Ensemble; however, it shows drastically different results than Analogy or MLR models.

6. Conclusions and extensions

The Bass model is one of the most popular models for forecasting market acceptance of a new product/service in terms of flexibility with three parameters and is suitable for predicting the introduction of new products in analogy with existing ones. However, parameter estimation has been a sticking point in this context because limited time series data is available for new products. However, a database with product characteristics and the newly parameterized values of the Bass model is one of the proposed solutions.

This paper proposed an approach based on a statistical algorithm and machine learning to predict the product's demand before its launching based on the Bass model. Using the Delphi and AHP method, we make the product attribute database, and we use them as input and the database of product diffusion as output. We built a prediction model using six machine learning algorithms. Then, we use ensemble models based on those 11 general prediction models to improve predictive power. At this stage, we cannot test on real data if our prediction models outperform the traditional analog method. The set model further enhances the accuracy of predictions. Applying an illustrative example of MicroLED, we also showed some application of possible models in practice. This paper contributes to a pre-launch prediction by proposing a new approach that uses statistical regression and machine learning algorithms. The proper use of statistical regression and machine learning algorithms can reliably map the relationship between existing products' attributes and diffusion characteristics, predicting new products' demand. With many market intelligence and transaction data, we can make the most of those three models, especially obtaining additional product demand data and attribute databases.

We have built and evaluated 11 regression models that use product properties to predict the Bass Model's p and q. Those are representative regression algorithms widely used in economics, statistics, and machine learning; namely Multiple Linear Regression (MLR), Ridge Regression, Lasso Regression, Classification and Regression Tree (CART), Random Forests, AdaBoost, Gradient Boosting Regressors (GBR), Extreme Gradient Boosting Regressors (XGBR) and Deep Learning using TensorFlow and Keras. As a result of evaluating a single regression model's predictive performance, the Random Forest and Deep Learning Regression show the best predictive performance in terms of three evaluation indicators of NMSE. After many experiments, as for single models, KNN and Lasso CV showed excellent predictive performance. We might not have had enough data to take advantage of other models since SVR, CART, and Boosting need a sufficient number of learning data to secure a certain level of generalization and performance.

Finally, we select four European countries to provide an application. We estimate the Product Life Cycle (PLC) of MicroLED in these four countries. Then we compare all results and best results of the sorts with MLR predictions and provide some conclusions. Based on Looks as we see mid-2028 as takeoff, early 2031 as peak, and late 2033 as accumulation. The best ensemble model (Random Forest) predicts those points a bit earlier since it predicts mid-2024 as takeoff, early 2026 as peak, and late 2029 as accumulation. Deep Learning predicts the most rapid MicroLED life cycle, the leap season when demand starts to increase in earnest in 2.4 years, meaning in mid-2024. The current top market is five years and is expected in 2025 when the maximum order is about 8.9 million TVs. The saturation period was seven years and was predicted later in 2027.

Estimating the coefficient of innovation p and imitation q using Look-like (comparative inference method) shows similar or lower prediction accuracy than KNN and Lasso CV, with the most moderate prediction accuracy among the single regression models. The Look-like process produces about twice as much error as the best multilinear regression model among individual regression models, and the prediction error is about ten times larger than the best ensemble regression model, Random Forest. This fact indirectly shows that our Bass Model parameter estimation framework using the Random Forest ensemble or Deep Learning that we used in this paper can is quite reliable.

Some highly sophisticated algorithms with high predictive power in machine learning show relatively low performance. Artificial Neural Networks, Regression Trees, and Support Vector Regression require sufficient learning data to ensure generalization performance. The total number of products used in this paper is 174, which means that the records might not be the optimal fit for some of the algorithms' profitable operations. Therefore, future studies could improve predictive models' performance by acquiring demand data for a more significant number of products and building a product database. We think that the Big Data world's advent and readily available PoS data by the private/public sector will improve. To update the product database periodically, we can imagine an Assisted intelligence system that learns product attributes from the existing database and assists a panel of experts by regularly getting feedback.

An additional point is related to the variables selected as product attributes since they might not be exhaustive. Although we already use 23 variables in this paper, they may not be sufficient to explain the specific characteristics of the spread of different products. Therefore this might also be regularly reviewed and updated. For example, essential variables may also vary depending on the country or the context of the industry. Thus further exploratory studies could help identify context-specific factors affecting product distribution.

Once adjusted the innovation and imitation parameters, we use data from the OECD to determine the four countries' potential market size in the application. We extrapolated m using the number of households taken from OECD statistics and latent demand per household. To predict only the product life cycle curve, the coefficients of innovation and imitations are sufficient. However, information on the potential market size is needed to make more accurate demand forecasting. Since the possible market size is susceptible to microeconomic and macroeconomic factors such as income levels, regulations, and cultures in the launching countries, it is difficult to estimate it based on such a straightforward method. We could use alternative ways, as suggested in the literate. Although we only used the number of households, more accurate demand forecasting requires forecasting possible market size through other methods as customer preference-focused approaches using customer questionnaires, for instance. Alternatively, if we elaborate more on our method proposed in this paper, we first make a country-specific database and attributes using macroeconomic variables rather than micro variables. We can estimate a potential market size reflecting countries' specifics. So, our research could be broaden using any of the avenues suggested.

7. Appendix

A1. Attributes and characteristics of selected products

Detailed definitions of variables

Attribute Type(high)	#	Attribute Type(low)	Type	Description
Industry characteristics	a	Industry classification	G	Electronic(G) and Others
	b	Industry classification	E	Electrical(E) and Others
	c	Industry classification	M	Mechanical(M) and Others
	e	Competition industry	MO	Monopoly(M)
	f	Competition industry	OL	Oligopoly(O)
	g	Competition industry	PE	Perfect Competition(P)
	h	Need and accessibility of substitution industry		5 points if more supplements are needed
	i	Level of existing complementary industry		5 points for more substitutes
Market characteristics	j	Average Selling Price		5 points for the highest price
	k	Level of potential demand		5 points for more demand
	l	horizontal/vertical integration of logistics channels		5 points for more channels
	M	Potential and Suppliers		5 points for more suppliers
Technological characteristics	n	Innovation factor	I	Progressive (I)
	o	Innovation factor	R	radical (R)
	p	Current change speed in the related field		5 points for faster change rate
	q	Accessibility (Imitation and Entry-level)		5 points easier to imitate
Product characteristics	r	Type of product	M	Required material (N)
	s	Type of product	N	luxury material (L)
	t	Difficulties and Need for learning		5 points for more learning
	u	Variety of use and application		5 points for more features
	v	Frequency of usage		5 points for the most frequency
	w	The average duration of usage		5 points for the most extended period
	x	Frequency of repurchase		5 points if more repeat purchases are possible

A.2. Products and attributes

#	Product	Industry classification :			Competition :			Need for Substitution goods	Level of existing complementary goods	Price	# of potential demand	# of logistics channel	# of suppliers	Innovation:		Speed of technology change	Accessabiltity(Imitation and Entry level)	Type of product:		Need for learning	Variety of use and application	Frequency of usage	Duriation of usage	Repeated Purchase	m	p	q
		G	E	M	MO	OL	PE							I	R			M	N								
1	PC Printers	1	0	0	0	0	1	4	5	3	2	1	2	1	0	2	1	1	0	3	5	2	2	3	6,663	0.0000	0.1738
2	Optical cable	1	0	0	0	0	1	5	4	4	2	2	3	1	0	2	2	0	1	3	1	1	3	5	735	0.0000	0.6118
3	Portable and Transportable Navigation	0	1	0	0	1	0	1	3	3	2	4	1	1	0	1	2	0	1	2	2	3	2	2	8	0.0001	0.8879
4	Press Machine	0	0	1	0	0	1	2	1	5	1	4	1	0	1	1	1	0	1	1	1	2	2	5	343	0.0002	0.4436
5	Car	0	0	1	0	1	0	4	2	5	2	1	1	0	1	4	3	0	1	5	5	1	3	3	1,808	0.0002	0.2182
6	Phone	1	0	0	0	1	0	1	2	2	2	4	2	0	1	5	2	0	1	4	5	5	1	5	15	0.0003	0.2672
7	Keyboard	0	0	1	0	0	1	5	2	3	1	2	4	1	0	1	1	0	1	4	1	2	3	3	913	0.0004	0.4890
8	DBS Satellite	1	0	0	0	0	1	2	1	5	2	1	2	0	1	5	3	1	0	2	5	2	3	4	244	0.0005	0.2539
9	Internal combustion engine for machinery	0	0	1	0	0	1	1	3	5	3	1	2	1	0	5	4	1	0	3	3	2	5	3	26,633	0.0005	0.1077
10	Mobile telephone	1	0	0	0	1	0	1	2	3	3	4	2	1	0	4	2	0	1	3	2	4	2	5	4,629	0.0006	0.4310
11	Mobile phone registration	1	0	0	0	1	0	1	2	2	2	4	2	1	0	3	3	0	1	3	2	4	2	5	15,077	0.0007	0.7003
12	elevator	0	0	1	0	0	1	3	4	5	2	2	2	1	0	3	4	1	0	5	2	2	5	2	40	0.0008	0.2273
13	Recorder	1	0	0	0	0	1	1	1	1	5	3	2	0	1	4	2	1	0	3	2	2	1	1	17,356	0.0009	0.2457
14	Digital TV Sets & Monitors	1	0	0	0	1	0	5	3	3	1	3	2	1	0	2	1	0	1	3	2	3	3	5	29	0.0010	0.5003
15	Portable MP3 Players	1	0	0	0	1	0	2	2	2	1	4	3	1	0	1	1	0	1	3	1	3	2	5	30	0.0011	0.6419
16	Dishwashers	0	1	0	0	0	1	1	3	4	2	1	1	1	0	5	5	1	0	4	4	1	3	1	9,968	0.0011	0.1419
17	cellphone	1	0	0	1	0	0	1	1	1	2	4	2	1	0	4	3	0	1	3	1	5	2	4	4,943	0.0011	0.2667
18	Television	1	0	0	0	1	0	4	2	3	5	2	2	0	1	5	2	1	0	1	5	4	3	3	26,895	0.0012	0.2687
19	Plasma DTV	1	0	0	0	1	0	5	3	3	2	3	4	1	0	2	2	0	1	1	2	3	2	5	25	0.0013	0.5931
20	Domain registraion	1	0	0	0	0	1	4	2	4	2	2	3	1	0	2	2	1	0	2	1	1	3	5	876	0.0014	0.4115
21	Modems/Fax Modems	1	0	0	0	0	1	5	5	2	2	2	2	1	0	2	5	1	0	5	2	2	2	3	42	0.0014	0.1781
22	Electric fan	0	1	0	0	0	1	2	5	2	2	2	1	1	0	4	2	0	1	3	2	1	2	2	8,100	0.0015	0.1846
23	Washing machine	0	1	0	0	0	1	3	2	3	2	1	1	1	0	5	4	0	1	3	3	3	3	3	8,100	0.0015	0.1846
24	Food Disposers	0	1	0	0	0	1	3	2	3	1	2	1	1	0	5	3	1	0	3	5	1	2	1	13,631	0.0016	0.1083
25	Digital Cameras	1	0	0	0	1	0	5	5	3	3	5	3	1	0	4	2	1	0	3	1	3	3	3	31	0.0016	0.4404
26	Analog Color TV	1	0	0	0	0	1	4	3	3	1	2	2	0	1	5	2	0	1	1	3	4	3	3	26	0.0017	0.1628
27	Compact Audio Systems	1	0	0	0	0	1	3	2	3	2	2	3	1	0	3	3	1	0	2	1	3	3	2	15	0.0020	0.2295
28	Total CD Players	1	0	0	0	0	1	2	4	2	2	2	2	0	1	4	3	1	0	2	2	2	2	3	98	0.0020	0.2381
29	Air Conditioners	0	0	1	0	0	1	1	4	5	2	1	1	1	0	2	1	1	0	2	3	2	2	2	13,473	0.0025	0.1284
30	VCR Decks with Stereo	1	0	0	0	1	0	2	5	4	2	2	2	1	0	5	4	1	0	2	2	3	3	2	15	0.0025	0.2976
31	Electronic photocopier	0	0	1	0	0	1	2	5	4	2	1	2	1	0	5	3	1	0	3	2	1	3	2	584	0.0025	0.1875
32	Dehumidifiers	0	0	1	0	0	1	3	3	4	2	1	1	1	0	3	4	1	0	5	1	1	2	2	1,751	0.0026	0.1388
33	vending machine	0	0	1	0	0	1	2	4	5	1	1	1	1	0	3	5	1	0	3	4	2	2	2	82	0.0027	0.3173
34	Record player	1	0	0	0	0	1	2	4	2	2	2	2	0	1	3	4	1	0	2	2	2	2	3	30,080	0.0027	0.2420
35	Cordless Telephones	1	0	0	0	1	0	1	2	2	2	4	2	0	1	5	2	0	1	5	5	4	1	5	53	0.0027	0.2034
36	Cloth Dryers	0	1	0	0	0	1	2	3	4	4	2	1	1	0	4	5	1	0	1	3	2	3	2	14,614	0.0027	0.1018
37	VCR Decks	1	0	0	0	1	0	2	1	4	1	1	2	1	0	5	4	1	0	2	2	3	3	2	37	0.0028	0.1650
38	Key Phone	1	0	0	1	0	0	1	5	2	2	1	2	1	0	1	5	1	0	5	3	2	1	2	30,954	0.0034	0.0297
39	Electric rice cooker	0	1	0	0	0	1	3	4	2	2	1	2	1	0	3	2	0	1	3	5	1	2	3	14,126	0.0034	0.0983
40	Portable CD Equipment	1	0	0	0	0	1	2	2	2	2	2	2	0	1	5	2	1	0	2	1	3	2	2	48	0.0036	0.2644
41	Black and white TV	1	0	0	0	1	0	1	1	3	2	1	2	0	1	4	2	1	0	2	5	3	3	3	7,586	0.0036	0.3217
42	Electric Bed Coverings	0	1	0	0	0	1	5	5	2	2	2	1	1	0	4	3	1	0	5	3	1	2	3	15,428	0.0036	0.1282
43	Electric cultivator	0	0	1	0	0	1	5	5	5	3	2	2	1	0	2	2	0	1	5	4	2	5	1	1,458	0.0038	0.2308
44	Construction Crane	0	0	1	0	0	1	2	1	5	1	1	1	1	0	5	5	0	1	3	4	2	5	3	37	0.0039	0.1688
45	Analog Projection TV	1	0	0	0	0	1	5	5	3	2	1	2	1	0	4	2	1	0	2	2	4	3	3	219	0.0040	0.2563
46	Aftermarket PC Monitors	1	0	0	0	0	1	5	5	3	2	2	2	1	0	4	3	1	0	5	2	2	1	2	16	0.0040	0.2563
47	Video record player	1	0	0	0	0	1	3	2	3	4	2	2	1	0	5	4	1	0	1	5	1	2	2	16,165	0.0041	0.3189
48	Lawn Mowers	0	0	1	0	0	1	5	4	5	3	2	1	1	0	2	5	1	0	3	1	1	3	3	18,784	0.0043	0.1295
49	Electric refrigerator	0	1	0	0	1	0	3	4	3	1	2	2	1	0	1	5	0	1	1	2	2	3	4	9,819	0.0044	0.1218
50	Analog TV/VCR Combinations	1	0	0	0	0	1	3	4	4	1	2	1	1	0	1	4	1	0	2	1	1	2	2	53	0.0050	0.3531
51	Lathe/shelf	0	0	1	0	0	1	3	2	5	1	2	2	0	1	4	4	0	1	4	5	1	5	1	14	0.0059	0.1851
52	Freezers	0	1	0	0	0	1	5	1	4	2	1	1	1	0	5	3	1	0	5	2	2	2	2	7,207	0.0069	0.0775
53	Camcorders	1	0	0	1	0	0	2	3	3	1	2	3	0	1	2	5	1	0	4	1	2	3	2	171	0.0071	0.1193
54	Digital Projection Sets & Monitors	1	0	0	0	1	0	3	2	3	1	4	2	1	0	1	3	0	1	1	2	4	3	5	19	0.0072	0.6874
55	Telephone Answering Devices	1	0	0	0	0	1	4	5	2	1	1	2	1	0	5	5	0	1	4	5	1	1	3	39	0.0074	0.1898
56	Home Theater-in-a-Box	1	0	0	0	0	1	5	1	4	1	2	2	1	0	4	4	1	0	5	1	1	3	3	48	0.0080	0.3323
57	Analog Color TV with Stereo	1	0	0	0	0	1	5	3	3	2	2	2	0	1	5	2	0	1	1	3	4	3	3	23	0.0082	0.1991
58	Stove(Gas range)	0	1	0	0	0	1	5	1	3	3	1	2	1	0	4	5	0	1	2	5	2	3	3	5,502	0.0083	0.2372
59	Microwave oven	0	1	0	0	0	1	2	3	3	4	2	1	0	1	4	5	1	0	1	4	3	1	1	20,985	0.0091	0.1903
60	Aftermarket Remote controls	0	1	0	0	0	1	1	3	1	1	2	1	1	0	4	4	1	0	3	2	3	2	1	52	0.0093	0.2248

Figure 10 Products and attributes (1) 1~60

#	Product	Industry classification :			Competition :			Need for Substitution goods	Level of existing complementary goods	Price	# of potential demand	# of logistics channel	# of suppliers	Innovation:		Speed of technology change	Accessabiltity(Imitation and Entry level)	Type of product:		Need for learning	Variety of use and application	Frequency of usage	Duriation of usage	Repeated Purchase	m	p	q
		G	E	M	MO	OL	PE							I	R			M	N								
61	DVD Players /Recorders	1	0	0	0	1	0	2	1	3	3	4	5	0	1	2	1	1	0	1	2	3	3	2	24	0.0097	0.3630
62	Analog Handheld LCD Color TV	1	0	0	0	1	0	1	1	2	1	2	3	0	1	3	2	1	0	3	2	4	2	1	84	0.0099	0.1732
63	Video camera	1	0	0	1	0	0	2	3	3	1	2	3	0	1	2	2	1	0	4	2	2	4	2	614	0.0104	0.5308
64	Fax Machines	1	0	0	0	1	0	2	2	3	2	2	3	0	1	2	3	1	0	3	2	2	3	2	44	0.0110	0.2669
65	Blank Videocassettes	1	0	0	0	1	0	5	1	1	2	2	4	0	1	4	5	1	0	2	1	3	1	5	107	0.0111	0.1378
66	Monochrome TV	1	0	0	0	1	0	1	1	3	2	1	2	0	1	4	2	1	0	2	1	3	3	3	259	0.0113	0.0868
67	CDP	1	0	0	0	0	1	2	3	2	2	3	2	0	1	5	2	1	0	2	1	3	2	2	3,902	0.0128	0.1833
68	Rack Audio Systems	1	0	0	1	0	0	2	2	3	1	3	3	1	0	1	3	1	0	3	3	2	3	2	19	0.0133	0.3665
69	Corded Telephones	1	0	0	0	1	0	1	1	1	2	4	2	0	1	4	3	0	1	3	1	5	2	4	80	0.0138	0.1092
70	Family Radio Devices	1	0	0	1	0	0	2	2	3	2	3	3	1	0	1	3	1	0	3	1	3	4	2	14	0.0153	0.3807
71	Personal Computers	1	0	0	0	1	0	1	3	4	3	2	2	0	1	3	3	1	0	3	5	3	2	1	80	0.0159	0.1798
72	Portable Tape and Radio/Tape Players	1	0	0	0	0	1	2	2	2	1	2	2	0	1	3	3	1	0	2	1	3	2	2	27	0.0174	0.2328
73	LCD TV (Digital and analog)	1	0	0	0	1	0	1	4	3	2	4	5	0	1	5	2	0	1	1	2	5	3	3	132	0.0186	0.2457
74	Videocassette Players	1	0	0	1	0	0	5	3	3	2	1	2	0	1	4	5	1	0	2	2	3	2	1	61	0.0197	0.2856
75	MP3	1	0	0	0	1	0	2	1	2	1	4	2	0	1	2	2	1	0	2	1	4	2	2	401	0.0197	0.6979
76	Personal Wordprocessors	0	0	1	0	0	1	2	3	1	1	1	2	0	1	5	5	1	0	1	4	2	2	1	51	0.0206	0.2159
77	LCD Monitor	1	0	0	0	1	0	1	2	3	3	2	3	0	1	5	3	0	1	1	3	2	1	2	922	0.0214	0.6129
78	Analog Handheld LCD Monochrome TV	1	0	0	0	1	0	1	2	1	1	2	3	0	1	3	2	1	0	3	2	4	2	1	112	0.0218	0.1635
79	Electronic calculator	0	0	1	0	0	1	1	2	1	2	1	2	1	0	5	5	1	0	3	3	2	2	1	5,332	0.0238	0.2559
80	Facsimile	1	0	0	0	1	0	2	2	3	1	2	3	0	1	2	3	1	0	3	2	2	2	2	1,922	0.0242	0.2642
81	Ultrasound imaging	1	0	0	0	1	0	3	3	4	4	1	3	0	1	4	2	1	0	3	3	4	5	3	86	0.0000	0.5340
82	Mammography	1	0	0	0	1	0	3	3	4	2	1	3	0	1	3	2	1	0	3	3	2	5	3	57	0.0000	0.7290
83	CT scanners (50-99 beds)	1	0	0	0	1	0	3	3	5	2	1	3	0	1	3	2	1	0	3	3	2	5	3	58	0.0440	0.3500
84	CT scanners (>100 beds)	1	0	0	0	1	0	3	3	4	2	1	3	0	1	3	2	1	0	3	3	2	5	3	95	0.0360	0.2680
85	Oxygen steel furnace (USA)	0	0	1	0	1	0	3	2	5	3	2	2	1	0	3	2	1	0	4	2	3	5	1	61	0.0020	0.4350
86	Oxygen steel furnace (France)	0	0	1	0	1	0	3	2	5	3	2	2	1	0	3	2	1	0	4	2	3	5	1	88	0.0080	0.2790
87	Oxygen steel furnace (Japan)	0	0	1	0	1	0	3	2	5	3	2	2	1	0	3	2	1	0	4	2	3	5	1	81	0.0490	0.3330
88	Steam (vs. sail) merchant ships (UK)	0	0	1	0	0	1	3	4	3	2	2	2	1	0	2	4	0	1	2	2	4	5	2	87	0.0060	0.2590
89	Plastic milk containers (1 gallon)	0	0	1	0	0	1	3	3	3	2	2	2	1	0	1	5	1	0	1	1	5	5	3	100	0.0200	0.2550
90	Plastic milk containers (half gallon)	0	0	1	0	0	1	3	3	3	2	2	2	1	0	1	5	1	0	1	1	5	5	3	29	0.0000	0.2340
91	Stores with retail scanners (FRG, units)	1	0	0	0	1	0	3	3	2	5	3	2	1	0	3	3	1	0	3	3	5	5	1	16,702	0.0010	0.6050
92	Stores with retail scanners (Denmark)	1	0	0	0	1	0	3	3	2	5	3	2	1	0	3	3	1	0	3	3	5	5	1	2,061	0.0760	0.5400
93	Air Conditioners	0	0	1	0	0	1	1	4	5	2	1	1	1	0	2	1	1	0	2	3	2	2	2	61	0.0060	0.1850
94	Bed cover	0	1	0	0	0	1	2	3	1	4	3	3	1	0	2	5	1	0	1	2	5	5	1	72	0.0080	0.1300
95	Blender	0	1	0	0	0	1	2	4	2	3	3	3	1	0	3	3	0	1	3	2	3	3	3	55	0.0000	0.2600
96	Can opener	0	0	1	0	0	1	2	4	1	3	3	3	1	0	2	5	1	0	1	2	3	5	1	68	0.0500	0.1260
97	Electric coffee maker	0	1	0	0	0	1	3	4	2	3	3	3	1	0	3	3	0	1	3	2	3	3	3	100	0.0420	0.1030
98	Cloth Dryers	0	1	0	0	0	1	2	3	4	4	2	1	1	0	4	5	1	0	1	3	2	3	2	70	0.0090	0.1430
99	Washing machine	0	1	0	0	0	1	3	2	3	2	1	1	1	0	5	4	0	1	3	3	3	3	3	100	0.0160	0.0490
100	Coffee maker ADC	0	1	0	0	0	1	3	4	2	3	3	3	1	0	3	3	0	1	3	2	3	3	3	32	0.0770	1.1060
101	Curling iron	0	1	0	0	0	1	3	3	1	2	3	4	1	0	3	3	0	1	2	2	3	4	2	30	0.1010	0.7620
102	Dishwasher	0	1	0	0	0	1	1	3	4	2	1	1	1	0	5	5	1	0	4	4	1	3	1	48	0.0000	0.2130
103	Disposer	0	1	0	0	0	1	3	3	2	3	3	3	1	0	2	3	1	0	3	2	4	5	2	50	0.0000	0.1790
104	Fondue	0	1	0	0	0	1	3	4	2	3	2	3	1	0	2	4	0	1	2	2	2	4	2	5	0.1660	0.4400
105	Freezer	0	1	0	0	0	1	5	1	4	2	1	1	1	0	5	3	1	0	5	2	2	2	2	94	0.0190	0.0000
106	Frypan	0	0	1	0	0	1	4	4	2	4	4	4	1	0	3	3	1	0	1	4	5	3	3	66	0.1420	0.0000
107	Hair dryer	0	1	0	0	0	1	3	3	2	3	3	3	1	0	3	4	1	0	2	2	4	4	3	52	0.0550	0.3990
108	Hot plates	0	1	0	0	0	1	3	4	2	4	3	3	1	0	3	4	1	0	2	4	5	5	2	26	0.0560	0.0000
109	Microwave oven	0	1	0	0	0	1	2	3	3	4	2	1	0	1	4	5	1	0	1	4	3	1	1	92	0.0020	0.3570
110	Mixer	0	1	0	0	1	0	3	4	2	3	3	3	1	0	3	4	1	0	2	4	2	4	2	98	0.0000	0.1340
111	Power leaf blower (gas or electric)	0	1	0	0	1	0	2	3	2	2	2	2	1	0	2	4	0	1	2	3	2	4	2	26	0.0130	0.3150
112	Stove(Gas range)	0	1	0	0	0	1	5	1	3	3	1	2	1	0	4	5	0	1	2	5	2	3	3	64	0.0040	0.0650
113	Range, built-in	0	1	0	0	0	1	5	1	3	3	1	2	1	0	4	5	0	1	2	5	3	4	2	22	0.0480	0.0860
114	Electric refrigerator	0	1	0	0	1	0	3	4	3	1	2	2	1	0	1	5	0	1	1	2	2	3	4	100	0.0250	0.1260
115	Slow cooker	0	1	0	0	0	1	3	4	2	2	1	2	1	0	3	2	0	1	3	5	1	2	3	34	0.0000	1.1520
116	Steam iron	0	1	0	0	1	0	3	4	2	3	2	3	1	0	3	3	1	0	3	3	3	5	2	100	0.0310	0.1280
117	Toaster	0	1	0	0	0	1	3	5	1	2	3	3	1	0	3	4	0	1	3	2	3	4	2	100	0.0380	0.0000
118	Cable television	1	0	0	0	1	0	1	1	2	1	2	3	0	1	3	2	1	0	3	2	4	2	1	68	0.1000	0.0600
119	Calculators	0	0	1	0	0	1	1	2	1	2	1	2	1	0	5	5	1	0	3	3	2	2	1	100	0.1430	0.5200
120	Video camera	1	0	0	1	0	0	2	3	3	1	2	3	0	1	2	2	1	0	4	2	2	4	2	31	0.0440	0.3040

```

**Figure 11 Products and attributes (2) 61~120**
```

#	Product	Industry classification :			Competition :			Need for Substitution goods	Level of existing complementary goods	Price	# of potential demand	# of logistics channel	# of suppliers	Innovation:		Speed of technology change	Accessabiltity(Imitation and Entry)	Type of product:		Need for learning	Variety of use and application	Frequency of usage	Duration of usage	Repeated Purchase	m	p	q
		G	E	M	MO	OL	PE							I	R			M	N								
121	CD player	1	0	0	0	0	1	2	4	2	2	2	2	0	1	4	3	1	0	2	2	2	2	3	30	0.0550	0.3780
122	Mobile telephone	1	0	0	0	1	0	1	2	3	3	4	2	1	0	4	2	0	1	3	2	4	2	5	45	0.0080	0.4210
123	Cordless Telephones	1	0	0	0	1	0	1	2	2	2	4	2	0	1	5	2	0	1	5	5	4	1	5	68	0.0040	0.3380
124	Electric toothbrush	1	0	0	0	1	0	3	4	3	3	3	2	0	1	3	3	0	1	3	3	4	3	3	15	0.1100	0.5480
125	Home PC (millions of units)	1	0	0	0	1	0	1	3	4	3	2	2	0	1	3	3	1	0	3	5	3	2	1	26	0.1210	0.2810
126	Telephone Answering Devices	1	0	0	0	0	1	4	5	2	1	1	2	1	0	5	5	0	1	4	5	1	1	3	70	0.0250	0.4060
127	Black and white TV	1	0	0	0	1	0	1	1	3	2	1	2	0	1	4	2	1	0	2	5	3	3	3	97	0.1080	0.2310
128	Television, color	1	0	0	0	0	1	4	3	3	1	2	2	0	1	5	2	0	1	1	3	4	3	3	100	0.0590	0.1460
129	VCR	1	0	0	0	1	0	2	1	4	1	1	2	1	0	5	4	1	0	2	2	3	3	2	76	0.0250	0.6030
130	Telephone Answering Devices	1	0	0	0	0	1	4	5	2	1	1	2	1	0	5	5	0	1	4	5	1	1	3	87,758,275	0.0089	0.5344
131	Black and white TV	1	0	0	0	1	0	1	1	3	2	1	2	0	1	4	2	1	0	2	5	3	3	3	73,916,461	0.0116	0.4049
132	Camcorders	1	0	0	1	0	0	2	3	3	1	2	3	0	1	2	2	1	0	4	2	2	4	2	23,629,672	0.0244	0.4436
133	Cassette Decks	1	0	0	1	0	0	5	3	3	2	1	2	0	1	4	5	1	0	2	2	3	2	1	375,533,906	0.0168	0.2717
134	CD Players	1	0	0	0	0	1	2	3	2	2	3	2	0	1	5	2	1	0	2	1	3	2	2	306,000,845	0.0017	0.3991
135	Color TV	1	0	0	0	0	1	4	3	3	1	2	2	0	1	5	2	0	1	1	3	4	3	3	40,521,849	0.0001	0.6485
136	Digital Watches	1	0	0	0	1	0	2	4	1	2	4	3	0	1	4	3	0	1	3	1	5	2	4	259,566,726	0.0165	0.3542
137	Handheld Calculators	0	0	1	0	0	1	1	4	1	2	3	3	1	0	5	5	1	0	3	3	2	3	3	334,527,259	0.0051	0.4343
138	Laser Disc Players	1	0	0	0	0	1	2	3	2	2	3	2	0	1	5	2	1	0	2	1	3	2	2	3,210,222	0.0124	0.3143
139	Minicomputers	1	0	0	0	1	0	1	3	4	3	2	2	0	1	3	3	1	0	3	5	3	2	1	2,656,549	0.0011	0.2408
140	Aftermarket PC Monitors	1	0	0	0	0	1	5	5	3	2	2	2	1	0	4	3	1	0	5	2	2	1	2	6,539,736	0.0119	0.9950
141	PC Printers	1	0	0	0	0	1	4	5	3	2	1	2	1	0	2	1	1	0	3	5	2	2	3	14,634,144	0.0174	0.7871
142	Personal Computer	1	0	0	0	1	0	1	3	4	3	2	2	0	1	3	3	1	0	3	5	3	2	1	389,745,519	0.0021	0.1517
143	Portable Tape and Radio/Tape Players	1	0	0	0	0	1	2	2	2	1	2	2	0	1	3	3	1	0	2	1	3	2	2	190,829,081	0.0070	0.3603
144	Projection TV	1	0	0	0	0	1	5	5	3	2	1	2	1	0	4	2	1	0	2	2	4	3	3	20,841,265	0.0051	0.2063
145	Radio	1	0	0	1	0	0	2	2	3	2	3	3	1	0	1	3	1	0	3	1	3	4	2	33,271,758	0.0103	0.4537
146	Record player	1	0	0	0	0	1	2	4	2	2	2	2	0	1	3	4	1	0	2	2	2	2	3	32,852,725	0.0187	0.4332
147	VCR's	1	0	0	0	1	0	2	1	4	1	1	2	1	0	5	4	1	0	2	2	3	3	2	59,288,852	0.0064	0.7503
148	Monitors	1	0	0	0	1	0	1	2	3	3	2	3	0	1	5	3	0	1	1	3	2	1	2	249,864,190	0.0515	0.4714
149	Audio Home systems	1	0	0	1	0	0	2	2	3	1	3	3	1	0	1	3	1	0	3	3	2	3	2	356,791,304	0.0279	0.0777
150	Air Conditioners	0	0	1	0	0	1	1	4	5	2	1	1	1	0	2	1	1	0	2	3	2	2	2	156,151,352	0.0149	0.1919
151	Bluetooth Headset	1	0	0	0	1	0	3	4	3	4	3	3	0	1	4	4	0	1	2	4	3	3	4	38,068,711	0.2821	0.1622
152	Car Audio	1	0	0	0	0	1	3	2	3	2	2	3	1	0	3	3	1	0	2	1	3	3	2	43,660,244	0.0725	0.3962
153	COOKER	0	1	0	0	0	1	3	4	2	2	1	2	1	0	3	2	0	1	3	5	1	2	3	684,637,073	0.0063	0.0291
154	COOLING	0	0	1	0	0	1	1	4	5	2	1	1	1	0	2	1	1	0	2	3	2	2	2	724,175,638	0.0131	0.3019
155	Docking Fusion	1	0	0	0	1	0	3	4	3	2	3	2	0	1	3	3	0	1	3	3	3	3	2	6,991,964	0.1163	0.4552
156	DISHWASHERS	0	1	0	0	0	1	1	3	4	2	1	1	1	0	5	5	1	0	4	4	1	3	1	56,474,521	0.0361	0.1542
157	Notebook Computer	1	0	0	0	1	0	4	4	4	4	3	3	0	1	5	3	1	0	3	5	5	4	3	53,164,927	0.0422	0.8304
158	Photo Frames	1	0	0	0	1	0	2	4	2	2	2	2	0	1	3	3	0	1	2	3	3	3	3	13,148,356	0.0768	0.9459
159	LTV Flat	1	0	0	0	1	0	5	3	3	2	3	4	1	0	2	2	0	1	1	2	3	2	5	2,144,217,108	0.0179	0.2502
160	Set Top Boxes	1	0	0	0	1	0	5	3	3	1	3	2	1	0	2	1	0	1	3	2	3	3	5	30,552,858	0.1073	0.2752
161	TUMBLEDRYERS	0	1	0	0	0	1	2	3	4	4	2	1	1	0	4	5	1	0	1	3	2	3	2	20,092,539	0.0509	0.3811
162	VACUUMCLEANERS	0	1	0	0	1	0	4	3	3	4	3	4	0	1	4	3	1	0	3	4	5	4	4	233,547,358	0.0148	0.3935
163	WASHINGMACH	0	1	0	0	0	1	3	2	3	2	1	1	1	0	5	4	0	1	3	3	3	3	3	768,441,995	0.0122	0.2864
164	Network Storage	1	0	0	0	1	0	3	4	4	2	3	2	0	1	4	3	0	1	4	3	3	4	3	32,822,320,798	0.0002	0.0487
165	Mobile Headset Bluetooth	1	0	0	0	1	0	3	4	3	4	3	3	0	1	4	4	0	1	2	4	3	3	4	1,731,873,576	0.0310	0.3025
166	MICROWAVEOVENS	0	1	0	0	0	1	2	3	3	4	2	1	0	1	4	5	1	0	1	4	3	1	1	117,313,777	0.0179	0.3579
167	Multi Disc Drives	1	0	0	0	0	1	2	3	2	2	3	2	0	1	5	2	1	0	2	1	3	2	2	13,436,393	0.0174	1.2066
168	Loud Speaker	1	0	0	0	0	1	2	3	2	2	3	2	0	1	5	2	1	0	2	1	3	2	2	21,293,541	0.0058	0.4081
169	Docking Mini Speaker	1	0	0	0	0	1	2	3	2	2	3	2	0	1	5	2	1	0	2	1	3	2	3	36,390,736,661	0.0001	0.0932
170	DVD Players / Recorders	1	0	0	0	1	0	2	1	3	3	4	5	0	1	2	1	1	0	1	2	3	3	2	411,656,708	0.1232	0.2020
171	FREEZERS	0	1	0	0	0	1	5	1	4	2	1	1	1	0	5	3	1	0	5	2	2	2	2	4,714,515	0.0989	0.0725
172	Headset Headphone Fusion	1	0	0	0	1	0	3	4	3	4	3	3	0	1	4	4	0	1	2	4	3	3	4	4,855,388,532	0.0459	0.1815
173	cooktop	0	1	0	0	0	1	3	4	2	4	3	3	1	0	3	4	1	0	2	4	5	5	2	57,352,790	0.0488	0.3691
174	HSHP	1	0	0	0	1	0	3	4	2	4	3	4	1	0	3	4	0	1	2	3	3	3	3	70,229,071	0.1186	0.2977

Figure 12 Products and attributes (3) 121-174

A.3. Code

Python Code- the Bass Model estimation function (code to estimate p, q and m)

```
from scipy.optimize import leastsq
from scipy.optimize import curve_fit
import matplotlib.pyplot as plt
import numpy as np
from scipy.optimize import leastsq
from scipy.optimize import curve_fit
import matplotlib.pyplot as plt
import numpy as np
EX_S='MON'
# sales vector
Product=sheet_to_df_map[EX_S].iloc[:,1:2]
L=len(Product)
print(L)
#time intervals
t= np.linspace(1.0, L, num=L)
sales=Product[Product.columns[0]].values
#print(sales)
# cumulatice sales
c_sales=np.cumsum(sales)
print(c_sales)
# initial variables(M, P & Q)
vars = [60630, 0.03,0.38]

# residual (error) function
def residual(vars, t, sales):
   M = vars[0]
   P = vars[1]
   Q = vars[2]
   Bass = M * (((P+Q)**2/P)*np.exp(-(P+Q)*t))/(1+(Q/P)*np.exp(-(P+Q)*t))**2
   return (Bass - (sales))

# non-linear least square fitting
varfinal,success = leastsq(residual, vars, args=(t, sales))

# estimated coefficients
```

```
m = varfinal[0]
p = varfinal[1]
q = varfinal[2]
print(float(m),float(p),float(q))
#sales plot (pdf)
#time interpolation
tp=(np.linspace(1.0, L*10, num=100))/10
cofactor= np.exp(-(p+q) * tp)
#print(tp)
sales_pdf= m* (((p+q)**2/p)*cofactor)/(1+(q/p)*cofactor)**2
plt.plot(tp, sales_pdf,t,sales)
plt.title(EX_S+' Sales pdf')
plt.legend([EX_S+'Fit', 'True'])
plt.show()
# Cumulative sales (cdf)
sales_cdf= m*(1-cofactor)/(1+(q/p)*cofactor)
plt.plot(tp, sales_cdf,t,c_sales)
plt.title(EX_S+' Sales cdf')
plt.legend(['Fit', 'True'])
plt.show()
```

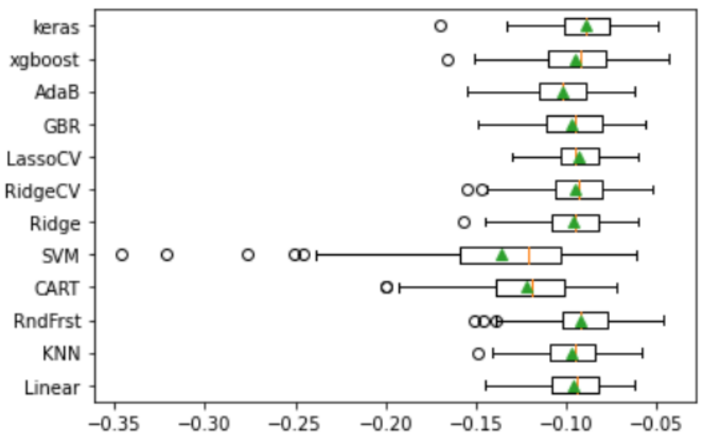
Estimation using 10 machine learning methods - all 10 linear, non-linear and ensembles (code to estimate p q m)

```
# get a list of models to evaluate
def get_models():
 models['Linear'] = LinearRegression()
 models['KNN'] = KNeighborsRegressor()
 models['RndFrst'] = RandomForestRegressor()
 models['CART'] = DecisionTreeRegressor()
 models['Ridge'] = Ridge()
 models['RidgeCV'] = RidgeCV()
 models['SVM'] = svm_wrapper
 models['LassoCV'] = LassoCV_wrapper
 models['GBR'] = GBR_wrapper
 models['AdaB'] = AdaB_wrapper
 models['xgboost']=xgboost_wrapper
 models['keras']= KerasRegressor(build_fn=baseline_model, epochs=50, batch_size=5, verbose=0)
 return models
```

```
# evaluate a given model using cross-validation , random_state=1
def evaluate_model(model):
  cv = RepeatedKFold(n_splits=10, n_repeats=10)
  scores = cross_val_score(model, X, y, scoring='neg_mean_absolute_error', cv=cv, n_jobs=-1, error_score='raise')
  return scores
# get the models to evaluate
models = get_models()
# evaluate the models and store results
results, names = list(), list()
for name, model in models.items():
  scores = evaluate_model(model)
  results.append(scores)
  names.append(name)
  print('>%s %.3f (%.3f)' % (name, mean(scores), std(scores)))


# plot model performance for comparison
pyplot.boxplot(results, labels=names, showmeans=True,vert=False)
pyplot.show()
```

Results:



Estimation using Deep Learning methods - (code to estimate p q m)

```
from pandas import read_csv

from keras.models import Sequential

from keras.layers import Dense

from keras.wrappers.scikit_learn import KerasRegressor

from sklearn.model_selection import cross_val_score

from sklearn.model_selection import KFold

from sklearn.preprocessing import StandardScaler

from sklearn.pipeline import Pipeline

# load dataset

#dataframe = read_csv("housing.csv", delim_whitespace=True, header=None)

#dataset = dataframe.values

# we split the data into input (X) and output (Y) variables

#X = dataset[:,0:13]

#Y = dataset[:,13]

# define base model

def baseline_model():

 # create model

 model = Sequential()

 model.add(Dense(13, input_dim=24, kernel_initializer='normal', activation='relu'))

 model.add(Dense(2, kernel_initializer='normal'))

 # Compile model

 model.compile(loss='mean_squared_error', optimizer='adam')

 return model

# evaluate model with standardized dataset


estimators = []

estimators.append(('standardize', StandardScaler()))

estimators.append(('mlp', KerasRegressor(build_fn=baseline_model, epochs=50, batch_size=5, verbose=0)))

pipeline = Pipeline(estimators)

kfold = KFold(n_splits=10)

results = cross_val_score(pipeline, X, y, cv=kfold)

print("Standardized: %.2f (%.2f) MSE" % (results.mean(), results.std()))

model=KerasRegressor(build_fn=baseline_model, epochs=50, batch_size=5, verbose=0)


# fit model

model.fit(X, y)
```

```
# make a prediction
data_in = X
yhat = model.predict(data_in)
# summarize prediction

df_Keras_yhat =pd.DataFrame(data=yhat[:],  columns=["p_hat", "y_hat"])
df_Keras_yhat.shape
df_Keras_yhat
```

Prediction of parameters for MicroLED - (code to estimate p q m)

```
data_in = X_microLED
yhat = model.predict(data_in)
print(yhat)
```

Prediction of parameters from Sales Database P, Q estimations with best algorithms

	Products	Estimates P					Estimates Q				
		MLR	Lasso CV	KNN	Random Forest	Deep Learning	MLR	Lasso CV	KNN	Random Forest	Deep Learning
1	Aftermarket PC Monitors	0.007948	0.023314	0.006764	0.013470	0.015448	0.625635	0.351837	0.354460	0.507713	0.327853
2	Aftermarket Remote controls	0.009300	0.004913	0.009940	0.008116	(0.008402)	0.224800	0.225334	0.277200	0.209885	0.194909
3	Air Conditioners	0.007792	0.016964	0.018610	0.009777	0.013418	0.168439	0.329790	0.220598	0.193929	0.236734
4	Analog Color TV	0.001700	0.000080	0.001760	0.004278	0.005890	0.162800	0.317722	0.251080	0.196540	0.236193
5	Analog Color TV with Stereo	0.008200	0.012233	0.008160	0.008081	0.008651	0.199100	0.342951	0.329260	0.218860	0.280943
6	Analog Handheld LCD Color TV	0.009900	0.016793	0.010060	0.018012	0.015033	0.173200	0.299722	0.311740	0.193574	0.260377
7	Analog Handheld LCD Monochrome TV	0.021800	0.021718	0.022180	0.020554	0.026980	0.163500	0.328133	0.398880	0.221857	0.278199
8	Analog Projection TV	0.004000	0.008539	0.003940	0.004270	0.005086	0.256300	0.327475	0.200220	0.249159	0.261017
9	Analog TV/VCR Combinations	0.005000	0.001835	0.004960	0.005583	0.003815	0.353100	0.358788	0.196000	0.321747	0.232975
10	Audio Home systems	0.027886	0.043573	0.028862	0.036628	0.048839	0.077695	0.392664	0.310543	0.253481	0.330591
11	Bed cover	0.008000	0.034477	0.027000	0.013085	0.046260	0.130000	0.223605	0.332200	0.153579	0.212125
12	Black and white TV	0.041057	0.025366	0.037990	0.037489	0.033283	0.319208	0.310590	0.300845	0.310887	0.272847
13	Blank Videocassettes	0.011100	0.025960	0.012000	0.012196	0.011872	0.137800	0.235341	0.156800	0.195919	0.249460
14	Blender	0.000001	0.032173	0.035400	0.016890	0.035039	0.260000	0.329021	0.345000	0.265292	0.273462
15	Bluetooth Headset	0.282103	0.052022	0.105733	0.212099	0.079176	0.162156	0.396122	0.302825	0.218798	0.371890
16	Cable television	0.100000	0.034031	0.074600	0.070402	0.039626	0.060000	0.338762	0.278000	0.160297	0.303738
17	Calculators	0.143000	0.031317	0.076000	0.099398	0.038505	0.520000	0.220733	0.252400	0.432057	0.225599
18	Camcorders	0.015755	0.026181	0.011121	0.018465	0.026028	0.281464	0.284256	0.373626	0.293831	0.280559
19	Can opener	0.050000	0.032481	0.021800	0.038695	0.049449	0.126000	0.290354	0.152400	0.161194	0.233826
20	Car	0.000200	(0.009406)	0.000240	0.001174	(0.005609)	0.218200	0.196946	0.273080	0.281579	0.138868
21	Car Audio	0.072516	0.047107	0.102730	0.057500	0.045025	0.396195	0.392074	0.256635	0.380234	0.348600
22	Cassette Decks	0.016832	0.035627	0.013608	0.028607	0.038716	0.271723	0.243465	0.473190	0.301877	0.279754
23	CD player	0.055000	0.031933	0.072000	0.047670	0.023321	0.378000	0.363756	0.434200	0.372037	0.331536
24	CD Players	0.001699	0.035935	0.011032	0.006656	0.027857	0.399084	0.409084	0.431958	0.413359	0.358891
25	CDP	0.012800	0.015311	0.012440	0.010942	0.010657	0.183300	0.362376	0.202540	0.227930	0.303095

26	cellphone	0.001100	(0.000079)	0.001040	0.003642	0.006809	0.266700	0.337778	0.540460	0.295969	0.295059
27	Cloth Dryers	0.005850	0.014901	0.020830	0.007764	0.009112	0.122400	0.213094	0.245140	0.145262	0.191777
28	Coffee maker ADC	0.077000	0.033713	0.047200	0.065368	0.037919	1.106000	0.333439	0.439800	0.804387	0.277023
29	Color TV	0.000100	0.033631	0.009516	0.020558	0.044491	0.648517	0.393710	0.397577	0.455102	0.345474
30	Compact Audio Systems	0.002000	0.008631	0.001960	0.002983	0.004628	0.229500	0.304932	0.273680	0.253912	0.221426
31	Construction Crane	0.003900	(0.000012)	0.003880	0.004791	(0.005708)	0.168800	0.183418	0.259300	0.176521	0.182848
32	COOKER	0.006255	0.041783	0.086524	0.020487	0.045016	0.029112	0.372284	0.228068	0.272532	0.285238
33	cooktop	0.048799	0.058794	0.067303	0.049241	0.073837	0.369096	0.272449	0.228710	0.317933	0.311077
34	COOLING	0.013120	0.036458	0.044607	0.018430	0.028867	0.301945	0.373942	0.274876	0.264558	0.294365
35	Corded Telephones	0.013800	0.015927	0.014120	0.012399	0.025243	0.109200	0.371707	0.198560	0.206731	0.288872
36	Cordless Telephones	0.003350	0.019005	0.031320	0.008961	0.028706	0.270700	0.354615	0.299640	0.313065	0.322316
37	CT scanners (>100 beds)	0.036000	0.026176	0.016400	0.026726	0.018567	0.268000	0.338783	0.463200	0.377823	0.307485
38	CT scanners (50-99 beds)	0.044000	0.025868	0.016400	0.028656	0.020438	0.350000	0.327820	0.463200	0.444854	0.309568
39	Curling iron	0.101000	0.037041	0.077200	0.083960	0.059251	0.762000	0.339579	0.518000	0.729053	0.262364
40	DBS Satellite	0.000500	(0.002850)	0.000420	0.002603	0.001241	0.253900	0.181501	0.255600	0.259117	0.175854
41	Dehumidifiers	0.002600	(0.001095)	0.002600	0.003591	(0.000616)	0.138800	0.208071	0.236640	0.164578	0.167919
42	Digital Cameras	0.001600	0.010627	0.001760	0.004133	0.009602	0.440400	0.445490	0.251080	0.421392	0.443697
43	Digital Projection Sets & Monitors	0.007200	0.008698	0.006380	0.010375	0.011362	0.687400	0.433945	0.296140	0.577053	0.276325
44	Digital TV Sets & Monitors	0.001000	(0.003614)	0.000940	0.003545	0.003041	0.500300	0.453858	0.573320	0.509979	0.575458
45	Digital Watches	0.016516	0.042182	0.007160	0.029275	0.057384	0.354246	0.426245	0.430093	0.400756	0.381679
46	Dishwasher	0.000001	0.020452	0.042000	0.009686	0.008314	0.213000	0.187724	0.169000	0.197629	0.238416
47	Dishwashers	0.018580	0.015527	0.025396	0.018912	0.011286	0.148033	0.176570	0.295450	0.192733	0.211788
48	Disposer	0.000001	0.034636	0.079800	0.017355	0.040215	0.179000	0.279849	0.577200	0.228887	0.259652
49	Docking Fusion	0.116269	0.042399	0.062808	0.098073	0.066391	0.455212	0.445360	0.531366	0.457163	0.374365
50	Docking Mini Speaker	0.000072	0.046708	0.038470	0.004254	0.035358	0.093228	0.431633	0.418288	0.273659	0.388210
51	Domain registration	0.001400	0.006476	0.001420	0.001698	0.002741	0.411500	0.361607	0.310380	0.407505	0.316537

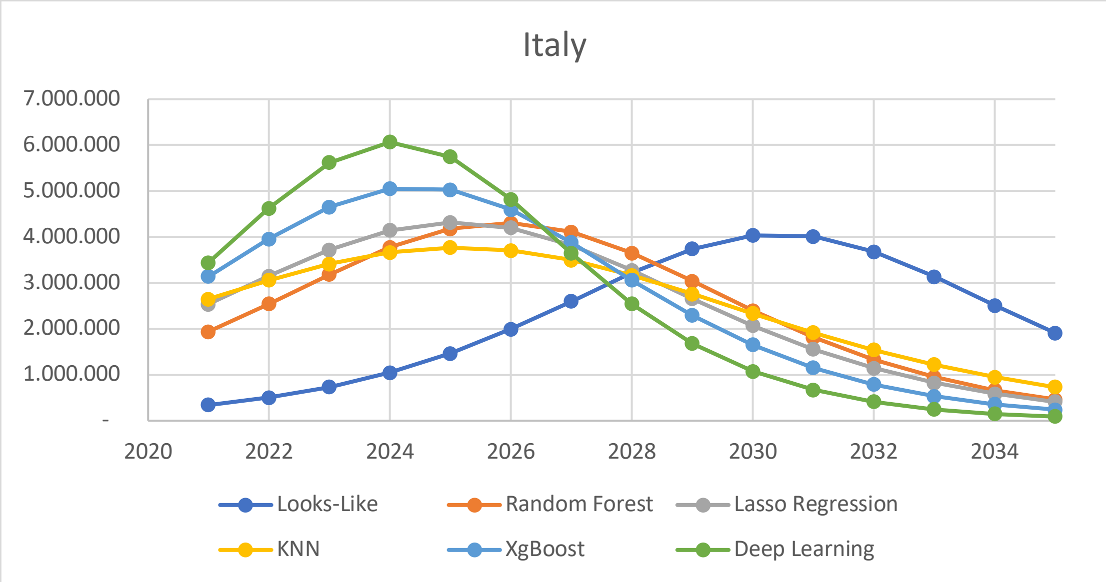
52	DVD Players /Recorders	0.066435	0.049748	0.024465	0.047787	0.061952	0.282503	0.431046	0.351214	0.328871	0.337279
53	Electric Bed Coverings	0.003600	0.001983	0.003760	0.005557	0.003924	0.128200	0.262127	0.193980	0.139275	0.210261
54	Electric coffee maker	0.042000	0.032789	0.054000	0.035651	0.035643	0.103000	0.331347	0.471400	0.232384	0.274675
55	Electric cultivator	0.003800	0.010535	0.003760	0.005036	0.010401	0.230800	0.312012	0.193980	0.236908	0.225315
56	Electric fan	0.001500	(0.004173)	0.001480	0.002865	0.001083	0.184600	0.355081	0.213420	0.212110	0.183075
57	Electric refrigerator	0.014700	0.017163	0.013500	0.018109	0.019415	0.123900	0.308747	0.313210	0.202257	0.212726
58	Electric rice cooker	0.003400	0.006692	0.003520	0.003153	0.003705	0.098300	0.292810	0.168460	0.216478	0.189158
59	Electric toothbrush	0.110000	0.035468	0.059600	0.087326	0.050482	0.548000	0.403297	0.393200	0.476345	0.350006
60	Electronic calculator	0.023800	0.019005	0.022360	0.024863	0.022373	0.255900	0.192847	0.302480	0.245555	0.194790
61	Electronic photocopier	0.002500	0.004230	0.002460	0.002674	0.005025	0.187500	0.250503	0.235860	0.192902	0.196289
62	Elevator	0.000800	(0.001619)	0.000820	0.001346	(0.000006)	0.227300	0.187718	0.335500	0.221669	0.238866
63	Facsimile	0.024200	0.022334	0.022760	0.022737	0.013254	0.264200	0.321197	0.352520	0.303053	0.280156
64	Family Radio Devices	0.015300	0.021867	0.015140	0.013341	0.012263	0.380700	0.346791	0.253800	0.368309	0.271677
65	Fax Machines	0.011000	0.020020	0.011180	0.011903	0.013385	0.266900	0.319426	0.284840	0.287989	0.264458
66	Fondue	0.166000	0.034944	0.079800	0.125370	0.041985	0.440000	0.324307	0.577200	0.398391	0.244296
67	Food Disposers	0.001600	(0.006168)	0.001660	0.003857	(0.003594)	0.108300	0.214946	0.173960	0.146993	0.167148
68	Freezer	0.019000	0.021376	0.048000	0.030783	0.006705	0.000001	0.223770	0.246200	0.122504	0.242416
69	Freezers	0.052884	0.023376	0.020095	0.035471	0.008190	0.075011	0.228302	0.302926	0.165472	0.241760
70	Frypan	0.142000	0.043803	0.083800	0.110761	0.067025	0.000001	0.280560	0.203600	0.151561	0.284038
71	Hairdryer	0.055000	0.035867	0.083800	0.052405	0.041875	0.399000	0.250602	0.203600	0.304446	0.256047
72	Handheld Calculators	0.005054	0.042490	0.007356	0.024448	0.054091	0.434303	0.281556	0.348556	0.437526	0.304745
73	Headset Headphone Fusion	0.045898	0.058486	0.067303	0.056745	0.084965	0.181516	0.410762	0.228710	0.217164	0.388061
74	Home PC (millions of units)	0.121000	0.035775	0.079600	0.075193	0.042712	0.281000	0.314511	0.355200	0.255435	0.320480
75	Home Theater-in-a-Box	0.008000	0.009314	0.007700	0.007289	0.008666	0.332300	0.296844	0.193080	0.300014	0.267301
76	Hot plates	0.056000	0.038786	0.053200	0.056152	0.050399	0.000001	0.227135	0.169600	0.087153	0.260880
77	HSHP	0.118577	0.064734	0.067303	0.099527	0.096049	0.297705	0.467033	0.228710	0.336136	0.392743

78	Internal combustion engine for machinery	0.000500	0.000069	0.000520	0.001426	(0.002411)	0.107700	0.160714	0.247620	0.147427	0.156137
79	Key Phone	0.003400	0.006385	0.002980	0.004174	0.002649	0.029700	0.219492	0.157820	0.108041	0.183458
80	Keyboard	0.000400	0.005496	0.000180	0.009691	(0.003478)	0.489000	0.311758	0.530100	0.460450	0.486477
81	LaserDisc Players	0.012432	0.037166	0.007160	0.010837	0.028960	0.314314	0.411873	0.430093	0.379016	0.361971
82	Lathe/shelf	0.005900	0.007775	0.005800	0.005794	0.002682	0.185100	0.198677	0.210780	0.209548	0.210963
83	Lawn Mowers	0.004300	0.006442	0.004340	0.004549	(0.000723)	0.129500	0.239353	0.223400	0.160977	0.190580
84	LCD Monitor	0.021400	0.026633	0.022360	0.020524	0.039053	0.612900	0.365294	0.302480	0.461343	0.283079
85	LCD TV (Digital and analog)	0.018600	0.034055	0.018180	0.017158	0.042082	0.245700	0.380923	0.379700	0.335405	0.353059
86	Loud Speaker	0.005779	0.046400	0.032873	0.009580	0.037230	0.408117	0.432787	0.453563	0.600288	0.385073
87	Mammography	0.000001	0.025561	0.020840	0.007141	0.018770	0.729000	0.337388	0.429040	0.611780	0.305100
88	Microwave oven	0.005550	0.020134	0.017080	0.008310	0.006399	0.273650	0.147754	0.222960	0.251053	0.182877
89	Microwave ovens XT	0.017910	0.045375	0.025909	0.026127	0.035198	0.357891	0.204919	0.506884	0.374725	0.245696
90	Minicomputers	0.001077	0.040085	0.007617	0.009133	0.046571	0.240831	0.324271	0.385654	0.240924	0.331260
91	Mixer	0.000001	0.036791	0.025200	0.025624	0.058658	0.134000	0.314152	0.241000	0.183361	0.265846
92	Mobile Headset Bluetooth	0.031034	0.056332	0.015240	0.047513	0.083035	0.302474	0.405882	0.277778	0.301354	0.382670
93	Mobile phone registration	0.000700	(0.001926)	0.000740	0.003162	0.005683	0.700300	0.383167	0.508140	0.605760	0.570677
94	Mobile telephone	0.004300	0.017615	0.022360	0.009082	0.025847	0.426000	0.443381	0.374910	0.429945	0.462209
95	Modems/Fax Modems	0.001400	0.001152	0.001420	0.002706	0.002439	0.178100	0.257851	0.310380	0.198649	0.201501
96	Monitors	0.051520	0.048487	0.077315	0.044224	0.063524	0.471449	0.414791	0.378957	0.498077	0.337880
97	Monochrome TV	0.011300	0.015003	0.011080	0.010480	0.010729	0.086800	0.329328	0.248200	0.144608	0.258861
98	MP3	0.019700	0.015162	0.020900	0.021707	0.023993	0.697900	0.390465	0.394260	0.536942	0.280556
99	Multi-Disc Drives	0.017433	0.046092	0.008275	0.014075	0.036954	1.206572	0.432090	0.422893	0.902763	0.384303
100	Network Storage	0.000180	0.045169	0.015145	0.022047	0.067979	0.048658	0.433620	0.447515	0.261790	0.407236
101	Notebook Computer	0.042241	0.053869	0.106442	0.062175	0.075208	0.830447	0.320604	0.557428	0.611690	0.398988
102	Optical cable	0.000001	0.000936	0.000140	0.000712	(0.004097)	0.611800	0.398451	0.521220	0.528933	0.647549
103	Oxygen steel furnace (France)	0.008000	0.023771	0.027800	0.009490	0.030316	0.279000	0.313431	0.333000	0.321540	0.258970

104	Oxygen steel furnace (Japan)	0.049000	0.024079	0.020200	0.033820	0.031175	0.333000	0.314128	0.314800	0.327360	0.259690
105	Oxygen steel furnace (USA)	0.002000	0.023463	0.027800	0.006790	0.029458	0.435000	0.312734	0.333000	0.391740	0.258249
106	PC Printers	0.008711	0.016542	0.003812	0.008892	0.015873	0.480463	0.374581	0.471618	0.458800	0.291914
107	Personal Computer	0.002103	0.041008	0.009255	0.010177	0.047398	0.151694	0.326362	0.394639	0.218019	0.333570
108	Personal Computers	0.015900	0.019154	0.016320	0.016832	0.018789	0.179800	0.276865	0.289080	0.201466	0.270604
109	Personal Wordprocessors	0.020600	0.015470	0.021460	0.018977	0.023958	0.215900	0.162136	0.306760	0.232752	0.178394
110	Phone	0.000300	(0.003465)	0.000460	0.002489	0.010238	0.267200	0.292823	0.374120	0.296412	0.299310
111	Photo Frames	0.076757	0.043322	0.072090	0.068890	0.066188	0.945864	0.442630	0.551382	0.769584	0.352352
112	Plasma DTV	0.001300	0.011801	0.001200	0.003971	0.001728	0.593100	0.414283	0.483100	0.543777	0.589589
113	Plastic milk containers (1 gallon)	0.020000	0.022083	0.015200	0.013318	0.023454	0.255000	0.214079	0.337200	0.238648	0.204556
114	Plastic milk containers (a half-gallon)	0.000001	0.022391	0.007000	0.005519	0.024213	0.234000	0.214776	0.296600	0.230458	0.205339
115	Portable and Transportable Navigation	0.000100	(0.010021)	0.000120	0.003244	(0.008616)	0.887900	0.367622	0.476860	0.729266	0.678945
116	Portable CD Equipment	0.003600	0.007000	0.003220	0.005775	0.004684	0.264400	0.313874	0.190240	0.245611	0.243853
117	Portable MP3 Players	0.001100	0.002326	0.001040	0.001539	0.004904	0.641900	0.469705	0.540460	0.598727	0.668866
118	Portable Tape and Radio/Tape Players	0.012188	0.025166	0.012913	0.016699	0.012854	0.296558	0.331004	0.331138	0.309821	0.289875
119	Power leaf blower (gas or electric)	0.013000	0.028855	0.019400	0.016413	0.058221	0.315000	0.353253	0.207800	0.300548	0.230904
120	Press Machine	0.000200	(0.012325)	0.000180	0.004998	(0.005847)	0.443600	0.343634	0.530100	0.468729	0.496999
121	Projection TV	0.005117	0.039013	0.012021	0.011587	0.036749	0.206263	0.396492	0.556381	0.356118	0.369283
122	PTV Flat	0.017891	0.054895	0.066610	0.034722	0.076415	0.250211	0.511882	0.463985	0.299516	0.383073
123	Rack Audio Systems	0.013300	0.018640	0.012740	0.013451	0.014956	0.366500	0.336196	0.256840	0.353056	0.264360
124	Radio	0.010337	0.044953	0.014053	0.023478	0.052655	0.453678	0.399077	0.415035	0.416167	0.331887
125	Range, built-in	0.048000	0.032082	0.013000	0.041520	0.053626	0.086000	0.203574	0.350400	0.136505	0.201669
126	Record player	0.010698	0.022391	0.010710	0.016130	0.016821	0.337614	0.312693	0.345633	0.338390	0.273984
127	Recorder	0.000900	0.006523	0.000880	0.004762	0.001318	0.245700	0.325848	0.457120	0.278784	0.183038

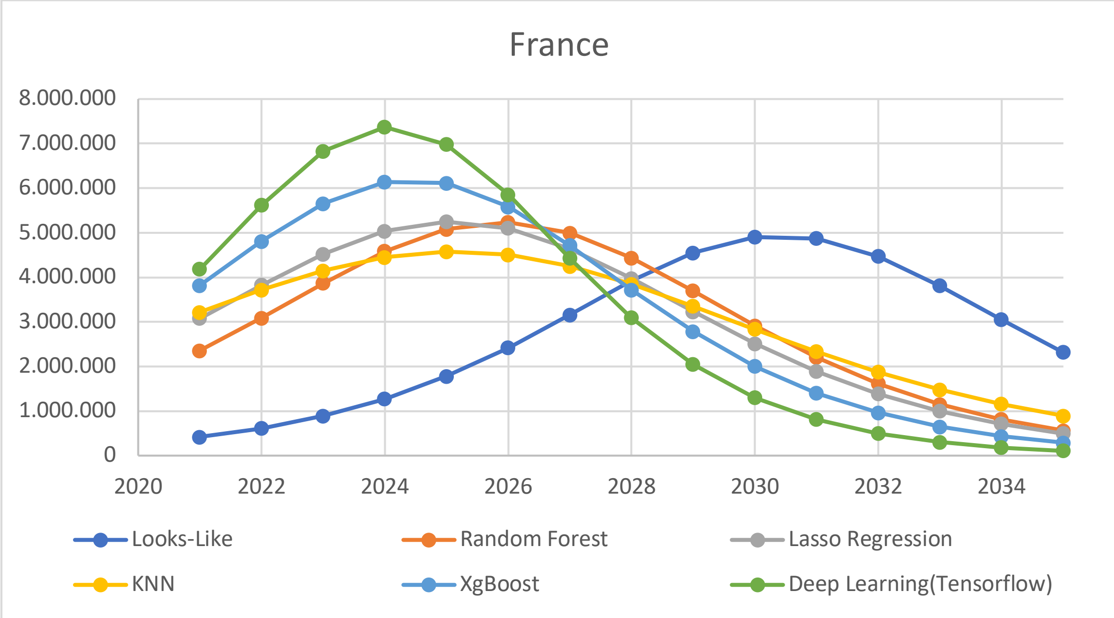
128	Set-Top Boxes	0.107293	0.041326	0.043392	0.081591	0.060467	0.275175	0.555640	0.382674	0.286699	0.394695
129	Slow cooker	0.000001	0.030086	0.021400	0.012114	0.034540	1.152000	0.345792	0.344200	0.779332	0.255977
130	Steam (vs. sail) merchant ships (UK)	0.006000	0.021775	0.016600	0.010409	0.028961	0.259000	0.296885	0.272000	0.256807	0.236095
131	Steam iron	0.031000	0.038638	0.027600	0.034191	0.057713	0.128000	0.312889	0.342000	0.281158	0.274638
132	Stores with retail scanners (Denmark, units)	0.076000	0.030840	0.017000	0.047944	0.039565	0.540000	0.384660	0.353800	0.543821	0.312641
133	Stores with retail scanners (FRG, units)	0.001000	0.030532	0.018200	0.020944	0.038807	0.605000	0.383963	0.353600	0.567221	0.311859
134	Stove(Gas range)	0.006150	0.023463	0.010600	0.012737	0.026517	0.151100	0.196791	0.290070	0.156115	0.182302
135	Telephone Answering Devices	0.013751	0.023986	0.033169	0.017042	0.021705	0.376747	0.320723	0.330287	0.372966	0.314988
136	Television	0.001200	0.008062	0.001300	0.003698	0.005126	0.268700	0.281079	0.344920	0.287894	0.201385
137	Television, color	0.059000	0.031476	0.062714	0.043393	0.042562	0.146000	0.388830	0.386585	0.275758	0.340084
138	Toaster	0.038000	0.036334	0.027600	0.048175	0.048920	0.000001	0.336749	0.342000	0.241656	0.288833
139	Total CD Players	0.002000	0.003306	0.002140	0.002499	0.002898	0.238100	0.298922	0.223100	0.237706	0.217938
140	Tumble Dryers	0.050928	0.043836	0.037773	0.043007	0.040693	0.381077	0.278625	0.454742	0.339943	0.268798
141	Ultrasound imaging	0.000001	0.030475	0.016400	0.002071	0.020034	0.534000	0.297281	0.463200	0.522623	0.308619
142	Vacuum Cleaners	0.014838	0.061040	0.020106	0.032629	0.079167	0.393463	0.230118	0.372290	0.348355	0.320138
143	VCR	0.025000	0.031784	0.045597	0.031752	0.040565	0.603000	0.331073	0.365710	0.542430	0.312199
144	VCR Decks	0.002800	0.003466	0.003080	0.003845	0.007028	0.165000	0.266936	0.218980	0.213242	0.227658
145	VCR Decks with Stereo	0.002500	0.003922	0.002340	0.003094	0.006991	0.297600	0.315396	0.254000	0.282390	0.244500
146	VCR's	0.006367	0.037325	0.022289	0.017315	0.045528	0.750258	0.343621	0.418589	0.634513	0.326060
147	vending machine	0.002700	(0.003398)	0.002600	0.003221	(0.002867)	0.317300	0.138043	0.236640	0.261217	0.162875
148	Video camera	0.027200	0.025874	0.032030	0.025386	0.025894	0.417400	0.329123	0.229070	0.391931	0.294211
149	Video record player	0.004100	0.014377	0.004060	0.007540	0.008620	0.318900	0.306292	0.225960	0.298067	0.231689
150	Videocassette Players	0.019700	0.017466	0.019760	0.015698	(0.005831)	0.285600	0.202334	0.409020	0.256909	0.233475
151	Washing machine	0.008750	0.007832	0.015230	0.010138	0.007546	0.116800	0.215465	0.248380	0.157027	0.188987
152	Washing+Dryer Combi	0.012238	0.039229	0.021844	0.019263	0.041068	0.286406	0.286573	0.282416	0.308392	0.273543

Prediction of MicroLED for Italy, France, Spain estimated parameters from best parameters



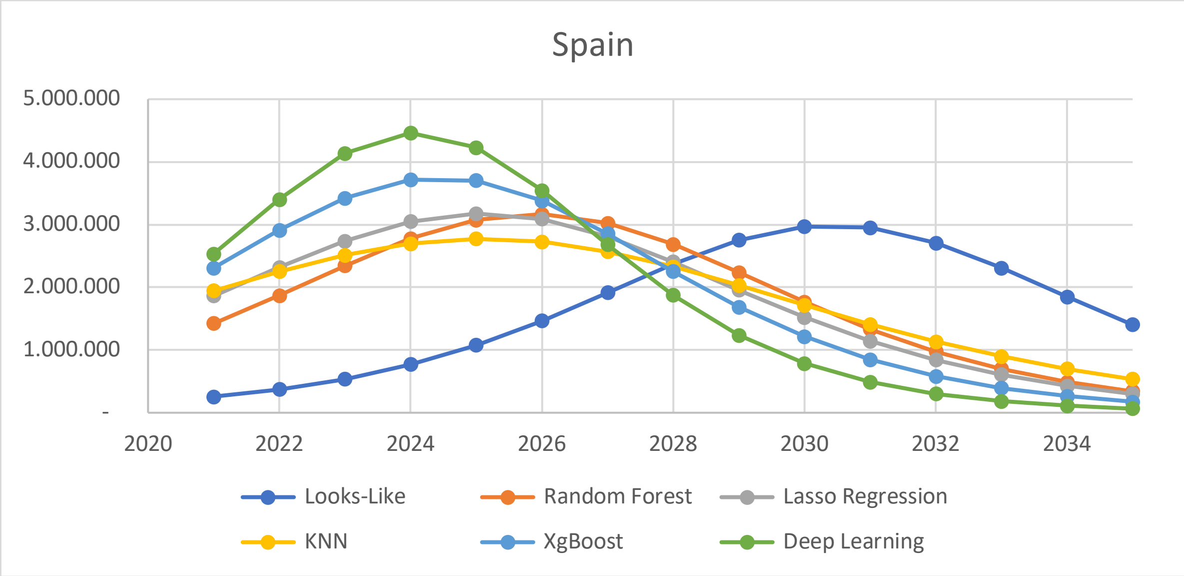
Italy

Year	Looks-Like	Random Forest	Lasso Regression	KNN	XgBoost	Deep Learning
2021	534,650	3,013,417	3,942,731	4,119,013	4,886,079	5,355,203
2022	784,179	3,952,520	4,900,314	4,762,676	6,152,706	7,193,385
2023	1,138,434	4,954,633	5,789,964	5,314,646	7,237,179	8,748,815
2024	1,628,335	5,869,769	6,445,847	5,700,222	7,858,782	9,435,622
2025	2,280,124	6,506,088	6,717,428	5,859,605	7,825,387	8,941,895
2026	3,099,478	6,700,186	6,535,473	5,766,255	7,147,884	7,495,087
2027	4,047,156	6,397,412	5,946,812	5,435,846	6,033,260	5,665,249
2028	5,015,003	5,682,039	5,090,546	4,920,918	4,763,094	3,958,286
2029	5,825,070	4,731,393	4,134,648	4,294,201	3,566,334	2,616,926
2030	6,277,494	3,732,689	3,217,355	3,629,026	2,566,100	1,667,753
2031	6,240,929	2,821,295	2,421,067	2,984,779	1,794,138	1,038,192
2032	5,726,508	2,064,139	1,776,310	2,400,653	1,229,423	636,888
2033	4,881,198	1,474,491	1,279,193	1,896,411	830,903	387,206
2034	3,906,695	1,035,380	908,885	1,476,919	556,343	234,122
2035	2,972,567	718,317	639,618	1,137,536	370,183	141,093
2036	2,176,174	494,185	447,096	868,685	245,290	84,859
2037	1,548,654	338,028	311,049	659,058	162,085	50,977
2038	1,080,047	230,303	215,689	497,546	106,909	30,601
2039	742,684	156,485	149,224	374,211	70,431	18,361
2040	505,764	106,133	103,077	280,658	46,362	11,014
2041	342,150	71,893	71,123	210,050	30,503	6,606
2042	230,431	48,659	49,038	156,956	20,062	3,962
2043	154,722	32,914	33,793	117,145	13,192	2,376
2044	103,678	22,256	23,279	87,354	8,673	1,425
2045	69,379	15,045	16,033	65,097	5,701	854
2046	46,385	10,168	11,040	48,487	3,748	512
2047	30,993	6,872	7,601	36,102	2,464	307
2048	20,700	4,643	5,233	26,873	1,619	184
2049	13,821	3,138	3,602	19,999	1,064	110
2050	9,227	2,120	2,480	14,881	700	66



France

Year	Looks-Like	Random Forest	Lasso Regression	KNN	XgBoost	Deep Learning(Tensorflow)
2021	417,619	2,353,800	3,079,694	3,217,389	3,816,549	4,182,985
2022	612,528	3,087,340	3,827,669	3,720,158	4,805,920	5,618,801
2023	889,239	3,870,097	4,522,580	4,151,306	5,653,009	6,833,758
2024	1,271,904	4,584,916	5,034,895	4,452,482	6,138,548	7,370,228
2025	1,781,020	5,081,949	5,247,028	4,576,977	6,112,462	6,984,574
2026	2,421,023	5,233,561	5,104,902	4,504,061	5,583,261	5,854,463
2027	3,161,261	4,997,061	4,645,095	4,245,976	4,712,620	4,425,164
2028	3,917,253	4,438,279	3,976,259	3,843,762	3,720,485	3,091,844
2029	4,550,001	3,695,723	3,229,601	3,354,229	2,785,688	2,044,098
2030	4,903,393	2,915,629	2,513,098	2,834,657	2,004,398	1,302,693
2031	4,874,831	2,203,732	1,891,112	2,331,431	1,401,413	810,939
2032	4,473,014	1,612,313	1,387,488	1,875,166	960,311	497,478
2033	3,812,737	1,151,735	999,186	1,481,299	649,024	302,449
2034	3,051,546	808,742	709,936	1,153,632	434,563	182,874
2035	2,321,892	561,082	499,610	888,537	289,152	110,208
2036	1,699,824	386,011	349,230	678,536	191,598	66,284
2037	1,209,664	264,036	242,963	514,795	126,606	39,818
2038	843,632	179,891	168,476	388,636	83,507	23,903
2039	580,116	122,232	116,560	292,299	55,014	14,342
2040	395,056	82,901	80,514	219,224	36,214	8,603
2041	267,256	56,156	55,555	164,071	23,826	5,160
2042	179,991	38,008	38,304	122,600	15,670	3,095
2043	120,855	25,710	26,396	91,503	10,304	1,856
2044	80,983	17,384	18,184	68,233	6,774	1,113
2045	54,192	11,752	12,523	50,848	4,453	667
2046	36,231	7,943	8,623	37,873	2,927	400
2047	24,208	5,368	5,937	28,199	1,924	240
2048	16,169	3,627	4,088	20,991	1,265	144
2049	10,796	2,451	2,814	15,622	831	86
2050	7,207	1,656	1,937	11,624	546	52

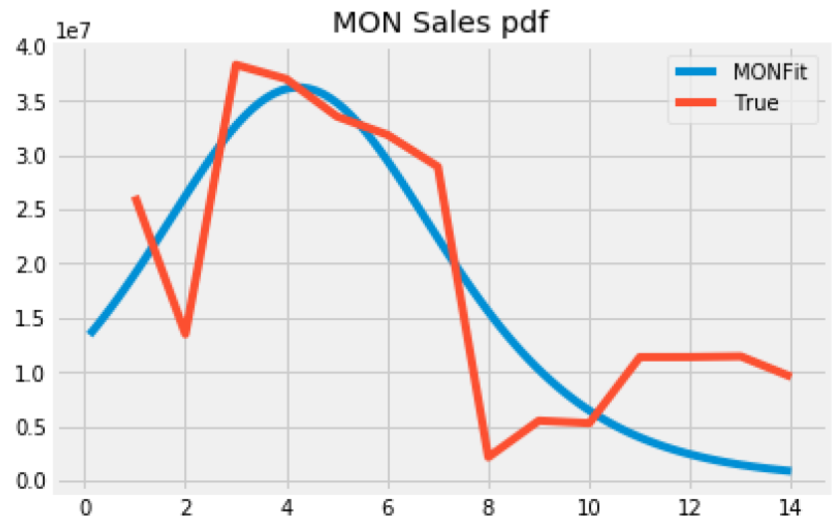


Spain

Year	Looks-Like	Random Forest	Lasso Regression	KNN	XgBoost	Deep Learning
2021	252,849	1,425,118	1,864,613	1,947,981	2,310,745	2,532,606
2022	370,857	1,869,243	2,317,478	2,252,385	2,909,764	3,401,926
2023	538,393	2,343,166	2,738,215	2,513,425	3,422,638	4,137,527
2024	770,079	2,775,956	3,048,398	2,695,774	3,716,609	4,462,335
2025	1,078,326	3,076,887	3,176,835	2,771,149	3,700,815	4,228,839
2026	1,465,818	3,168,681	3,090,784	2,727,002	3,380,408	3,544,608
2027	1,913,998	3,025,491	2,812,392	2,570,743	2,853,275	2,679,234
2028	2,371,717	2,687,174	2,407,443	2,327,222	2,252,583	1,871,969
2029	2,754,817	2,237,591	1,955,375	2,030,832	1,686,606	1,237,608
2030	2,968,779	1,765,279	1,521,565	1,716,254	1,213,571	788,721
2031	2,951,487	1,334,259	1,144,982	1,411,575	848,491	490,986
2032	2,708,205	976,182	840,060	1,135,327	581,424	301,200
2033	2,308,437	697,323	604,961	896,859	392,954	183,119
2034	1,847,571	489,656	429,834	698,471	263,108	110,722
2035	1,405,799	339,710	302,491	537,969	175,068	66,726
2036	1,029,166	233,712	211,443	410,822	116,004	40,132
2037	732,396	159,862	147,103	311,685	76,654	24,108
2038	510,781	108,916	102,005	235,301	50,560	14,472
2039	351,233	74,006	70,572	176,974	33,308	8,684
2040	239,188	50,193	48,748	132,730	21,926	5,209
2041	161,811	34,000	33,636	99,338	14,426	3,124
2042	108,976	23,012	23,191	74,229	9,488	1,874
2043	73,172	15,566	15,982	55,401	6,239	1,124
2044	49,032	10,525	11,009	41,312	4,102	674
2045	32,811	7,115	7,582	30,786	2,696	404
2046	21,936	4,809	5,221	22,931	1,772	242
2047	14,657	3,250	3,595	17,073	1,165	145
2048	9,789	2,196	2,475	12,709	766	87
2049	6,536	1,484	1,704	9,458	503	52
2050	4,364	1,003	1,173	7,038	331	31

Prediction of parameters from Sales Database - (some illustrative results.)

```
EX_S='MON'
M, P, Q =
(249864189.94223487, 0.05151967574263949, 0.4714490488093874)
```




```
EX_S='AHS'
M, P, Q =
(356791303.64978075,          0.02788578213009858,          0.07769514961922512
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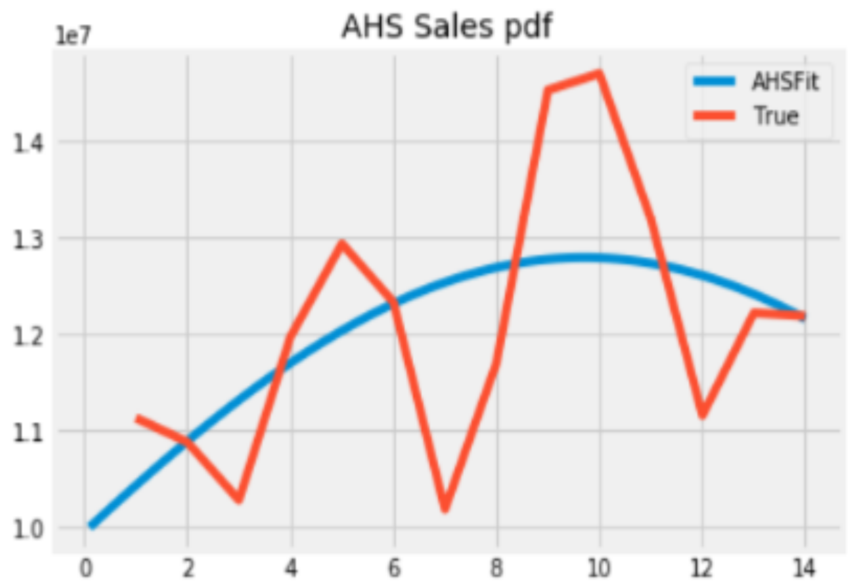


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EX_S='AIRCONDITION'
M, P, Q =
(156151352.28238058, 0.014875486193397668, 0.19191742747399926)
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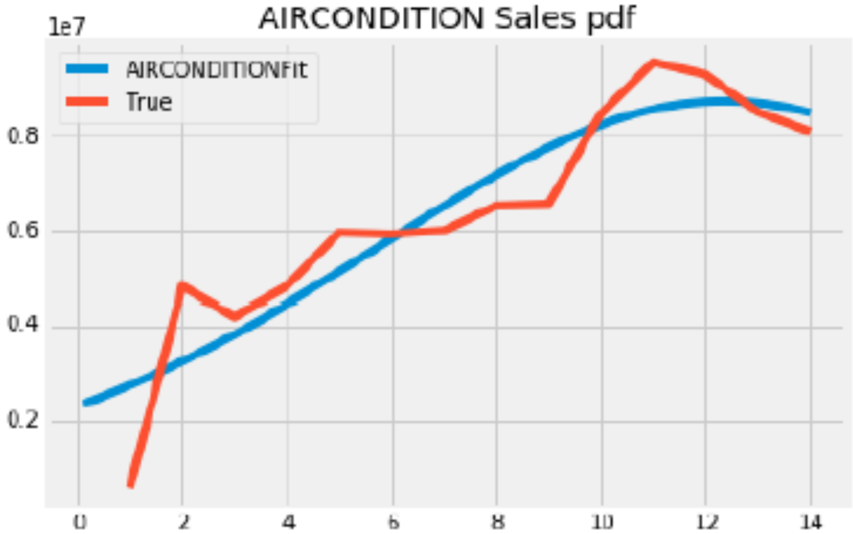
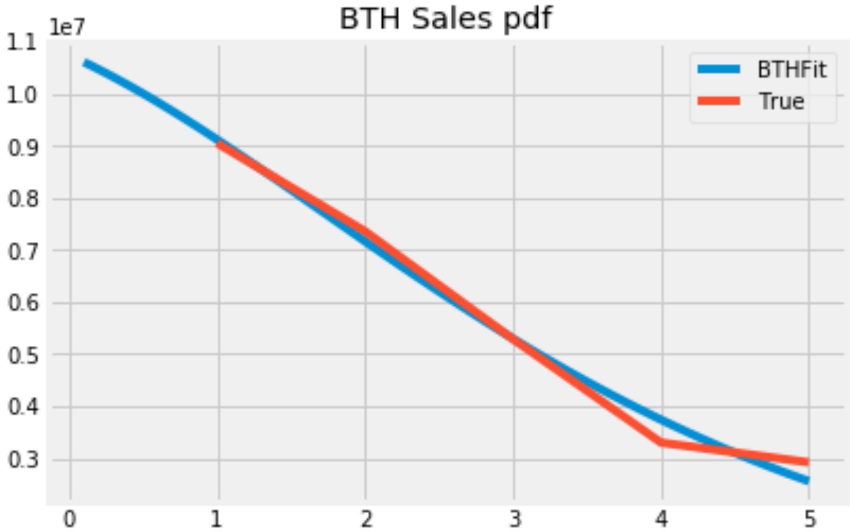


EX_S='BTH'

M, P, Q =

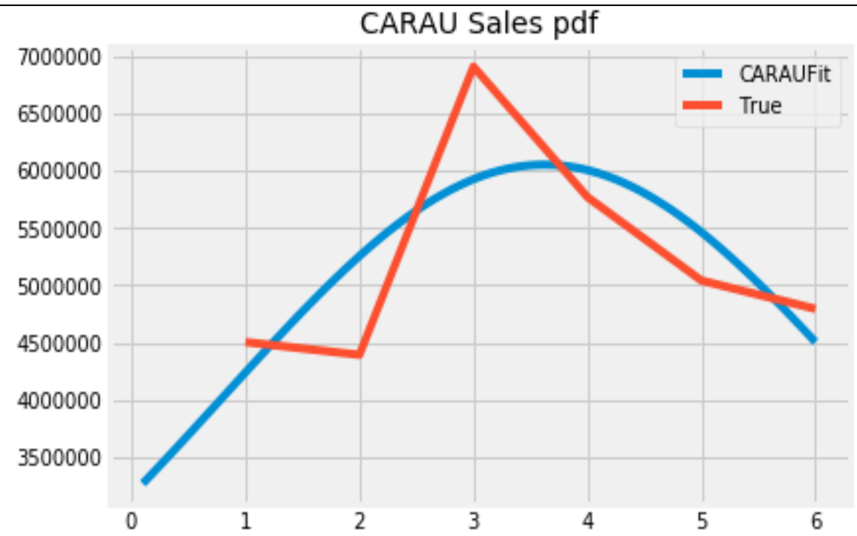
(38068710.82714332, 0.282103477744939, 0.16215642424015103)



EX_S='CARAU'

M, P, Q =

(43660243.559452735, 0.07251571989216345, 0.3961948363322243)

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EX_S='COOKER'
M, P, Q =
(684637073.440371, 0.006255462992589662, 0.02911226458289849)
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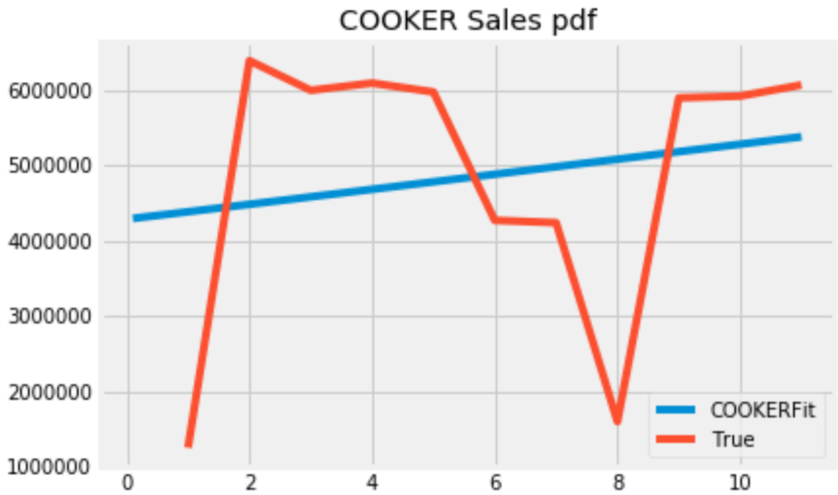


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EX_S='COOLING'
M, P, Q =
(724175638.1434642, 0.013119821918148885, 0.30194495845565533)
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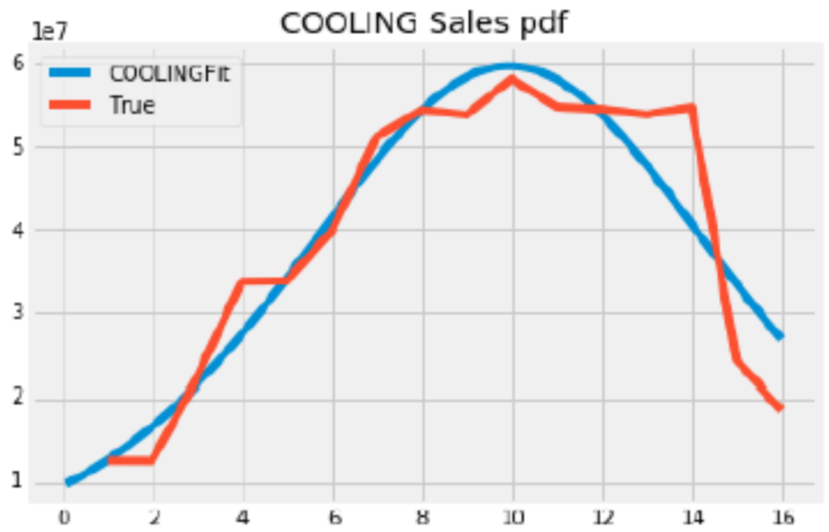
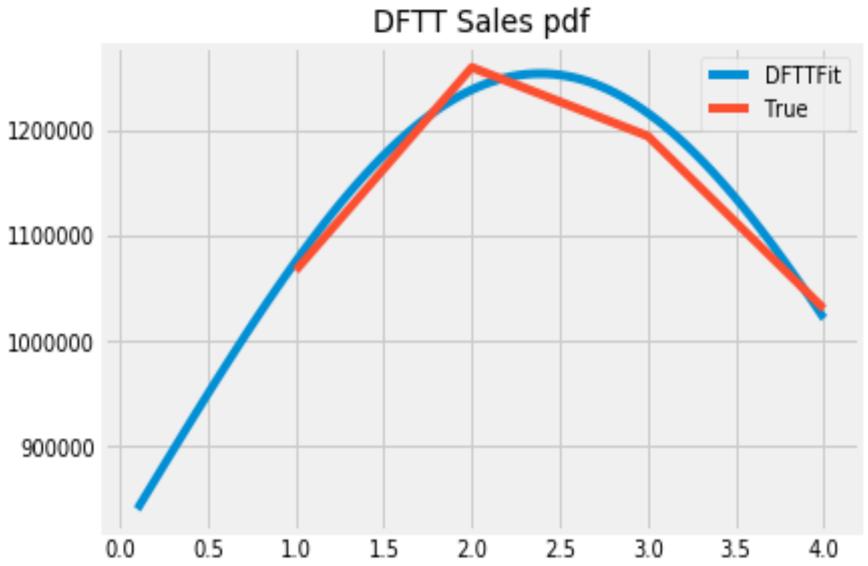


EX_S='DFTT'

M, P, Q =

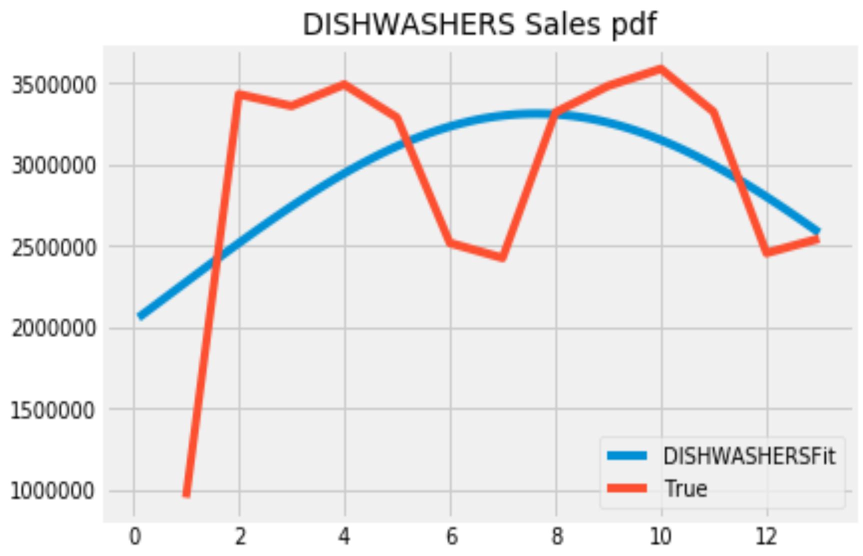
(6991963.736925167, 0.11626860348235142, 0.4552119931487289)



EX_S='DISHWASHERS'

M, P, Q =

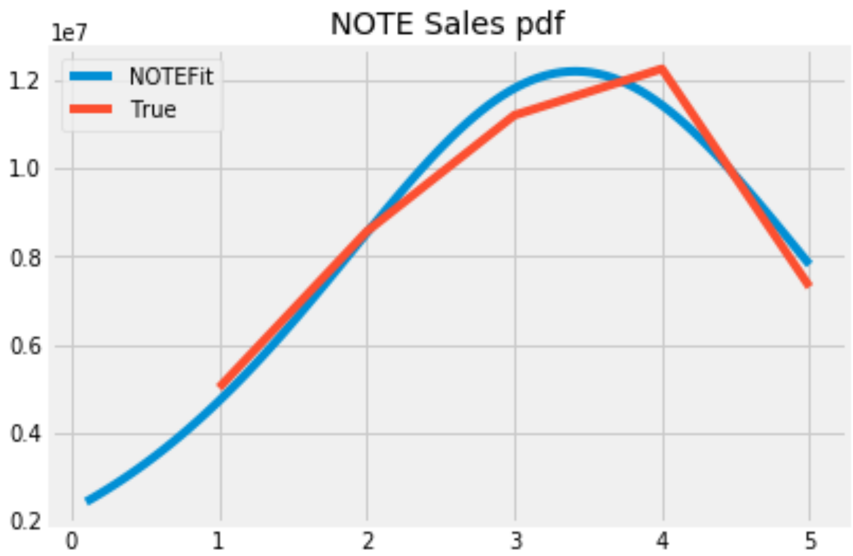
(56474520.747345015, 0.03606094944572672, 0.15416615592537744)



EX_S='NOTE'

M, P, Q =

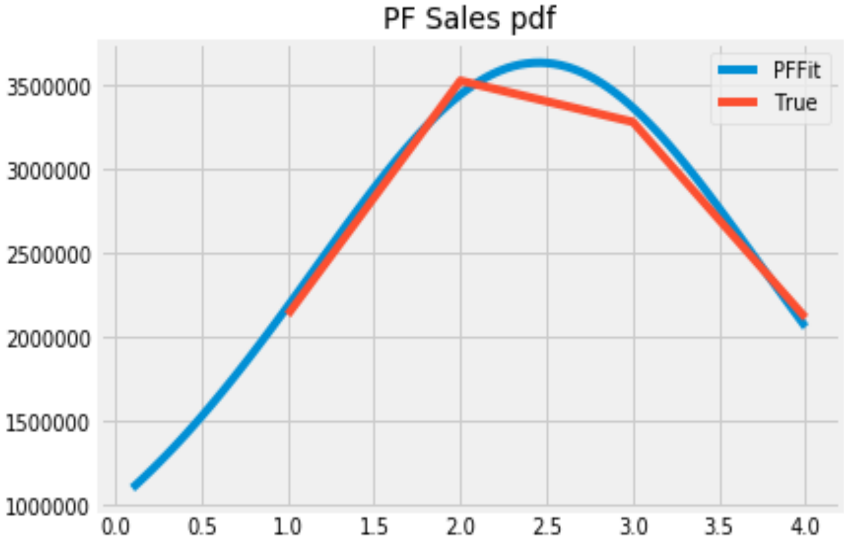
(53164927.26270969, 0.04224094458146507, 0.8304474059710198)



EX_S='PF'

M, P, Q =

(13148356.433202548, 0.0767566325694544, 0.9458643799372612)

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EX_S='PTV
M, P, Q =
(2144217108.2872765, 0.01789148839685046, 0.25021120542953335)
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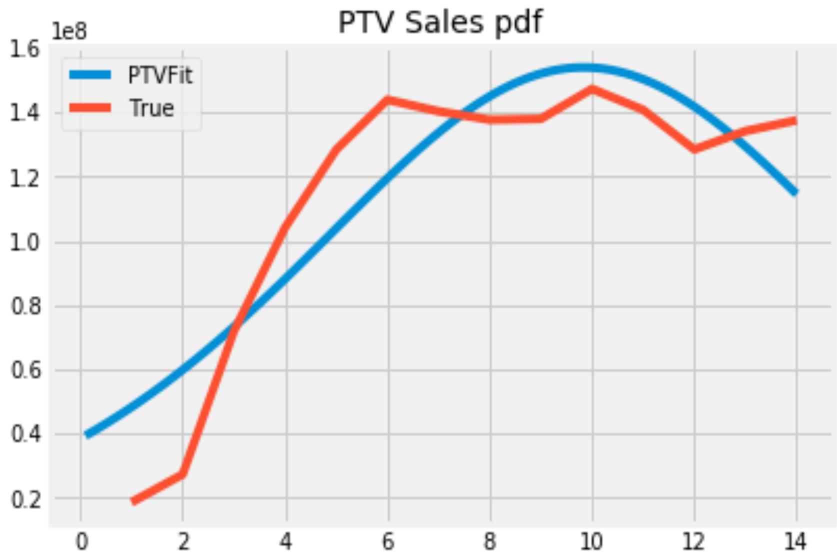


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EX_S='STB'
M, P, Q =
(30552858.46388939, 0.10729320593091968, 0.27517540661963835)
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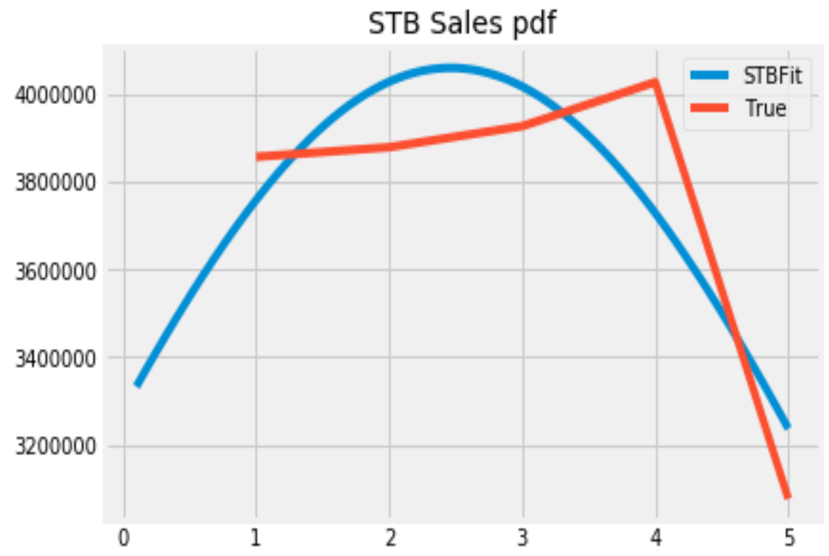
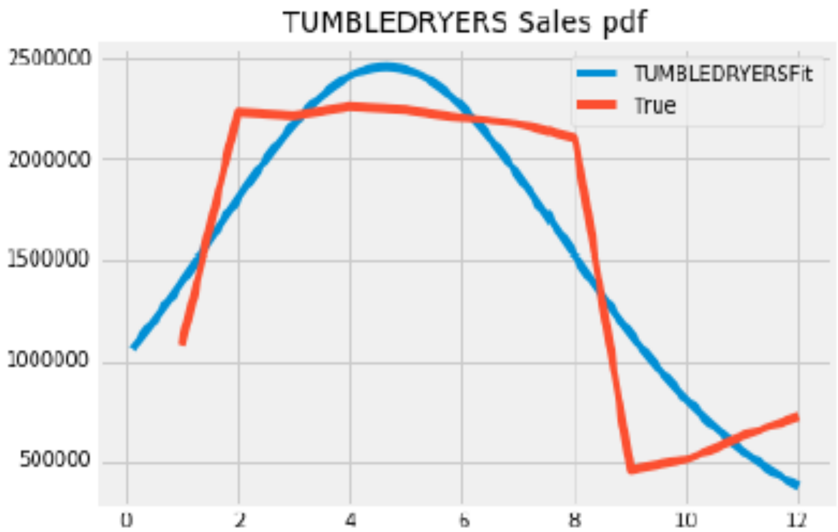


EX_S='TUMBLEDRYERS'

M, P, Q =

(20092538.63425862, 0.05092754299290764, 0.38107688315820554)



EX_S='TUMBLEDRYERS'

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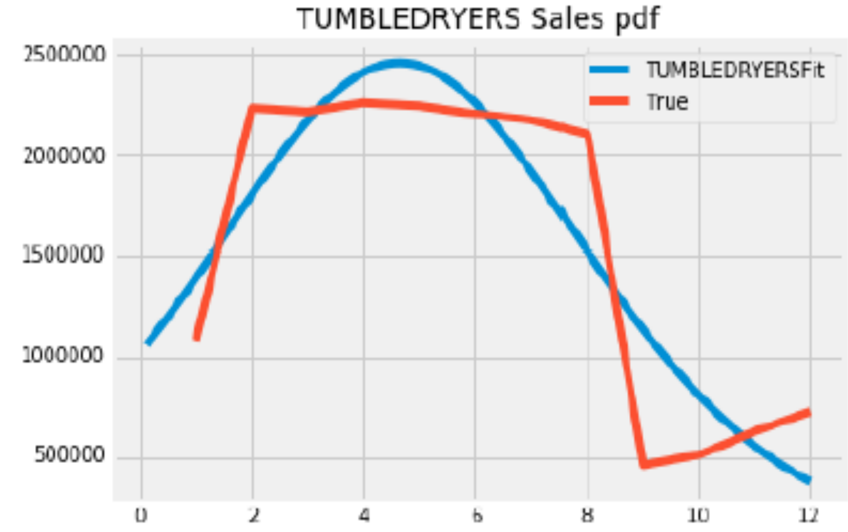
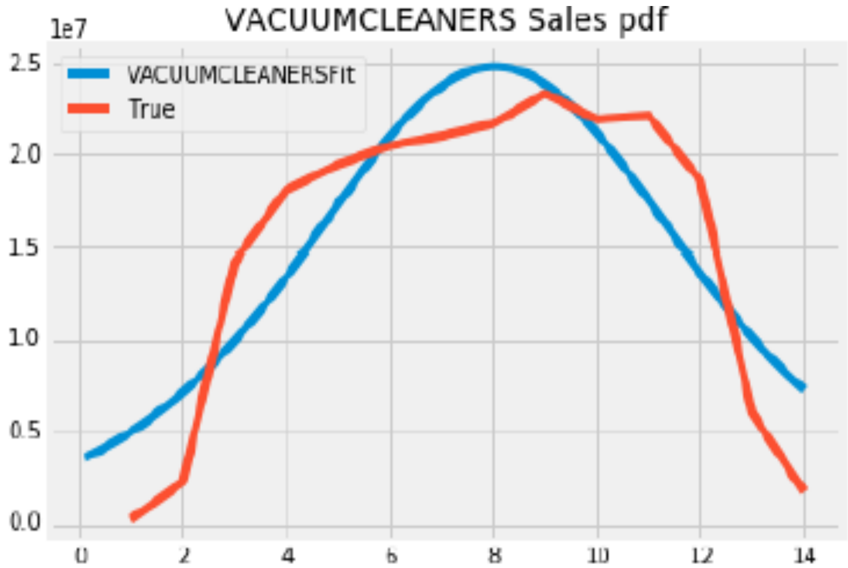
(20092538.63425862, 0.05092754299290764, 0.38107688315820554)



EX_S='VACUUMCLEANERS'

M, P, Q =

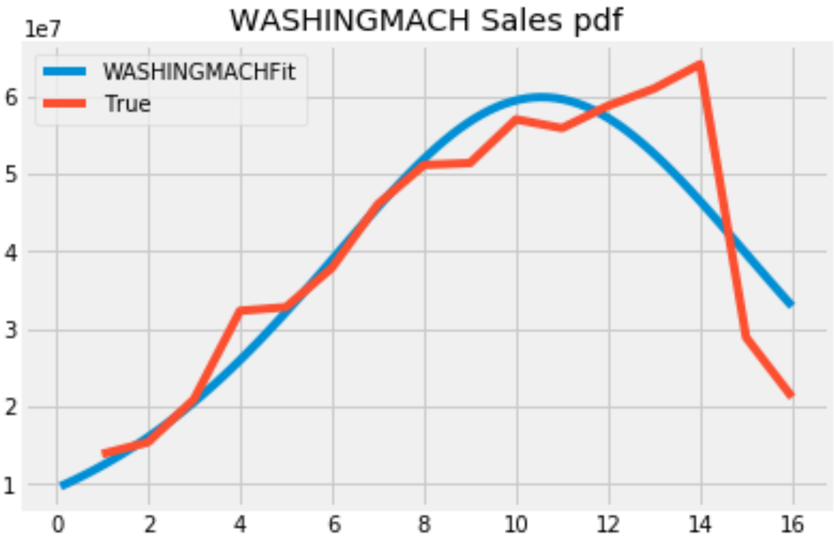
(233547357.64864814, 0.01483754917945439, 0.3934633601490733)



EX_S='WASHINGMACH'

M, P, Q =

(768441994.520374, 0.012238125969531851, 0.2864057459832784)

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EX_S='NAS'
M, P, Q =
(32822320797.729828, 0.00018010101386859597, 0.048657844823949456)
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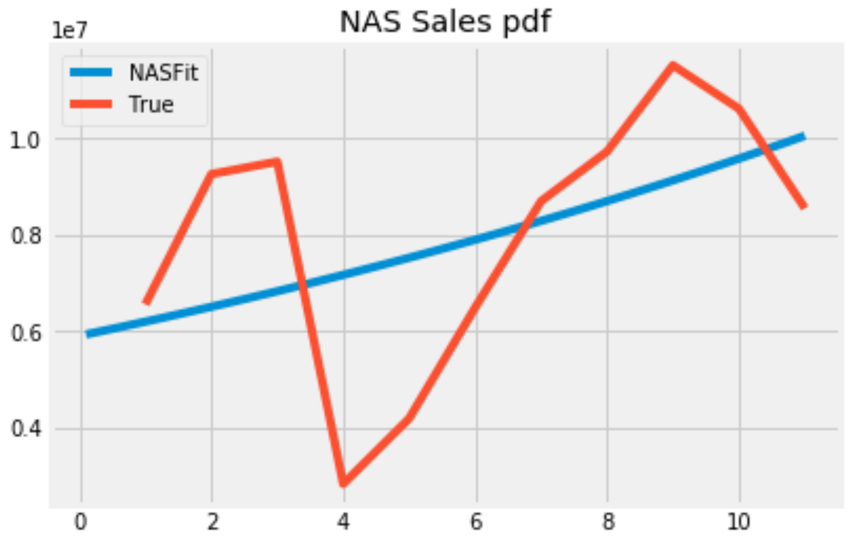
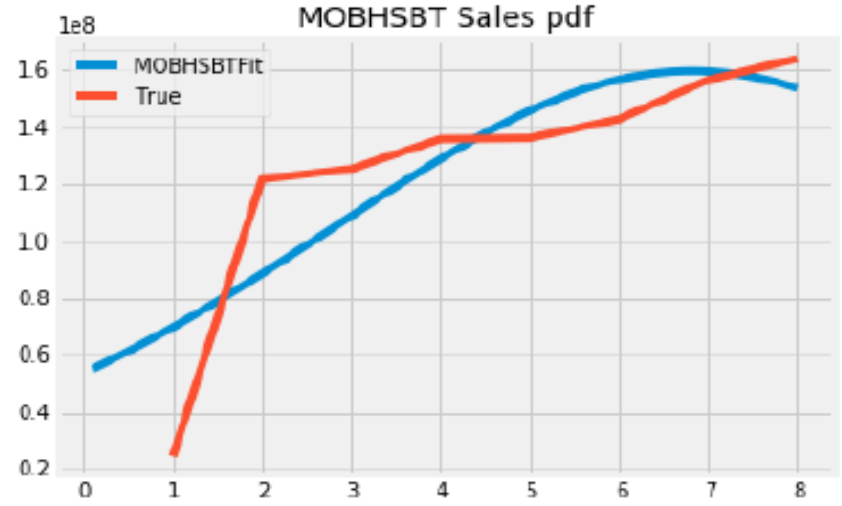



```
EX_S='MOBHSBT'
M, P, Q =
```

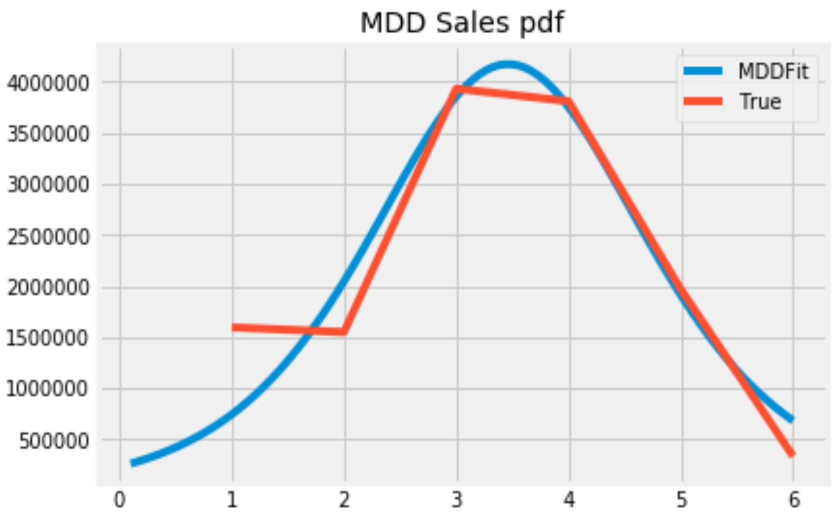
(1731873576.4982846, 0.031033580106292327, 0.3024736495411225)



EX_S='MDD'

M, P, Q =

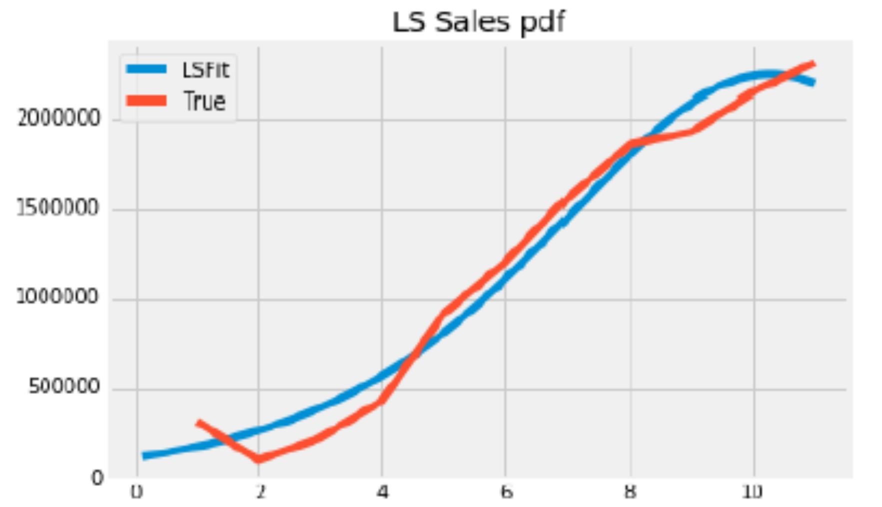
(13436392.508431775, 0.017432639473321968, 1.2065723955478889)



EX_S='LS'

M, P, Q =

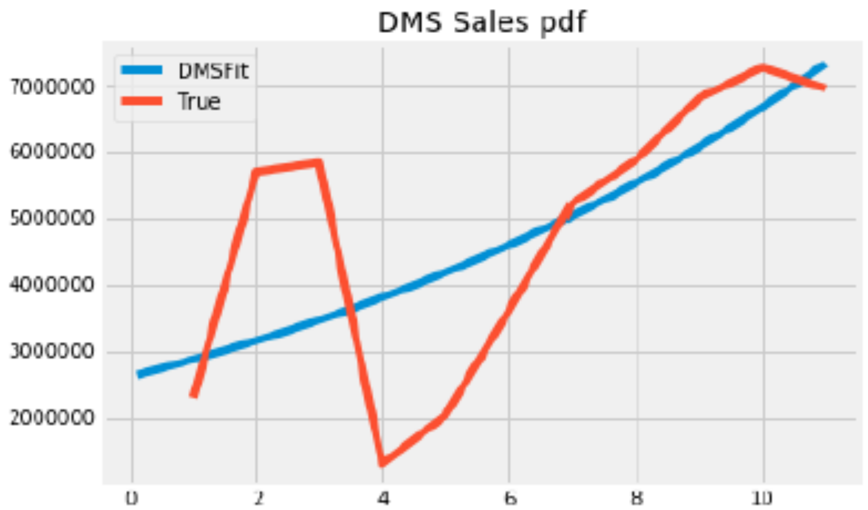
(21293540.983731117, 0.005779434399329891, 0.40811709003181423)



EX S='DMS'

M, P, Q =

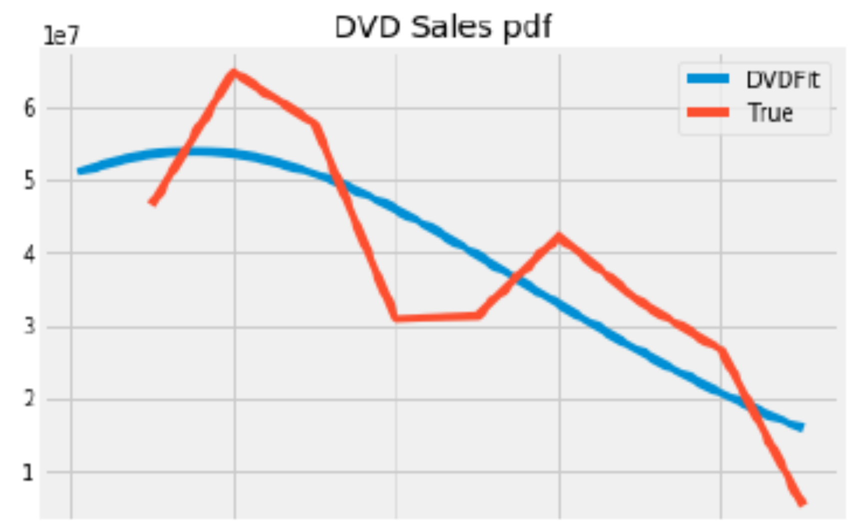
(36390736661.038864, 7.224020021671412e-05, 0.09322800231352293)



EX_S='DVD'

M, P, Q =

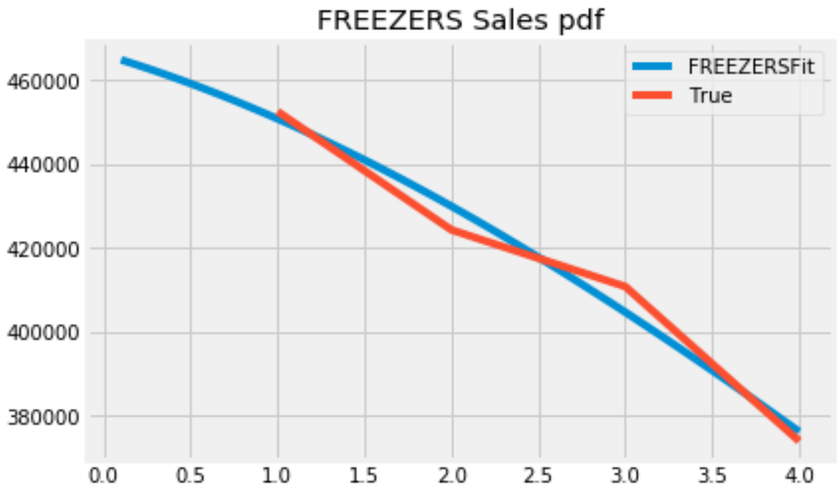
(411656707.92070144, 0.12316911272362466, 0.20200541916031628)



EX_S='FREEZERS'

M, P, Q =

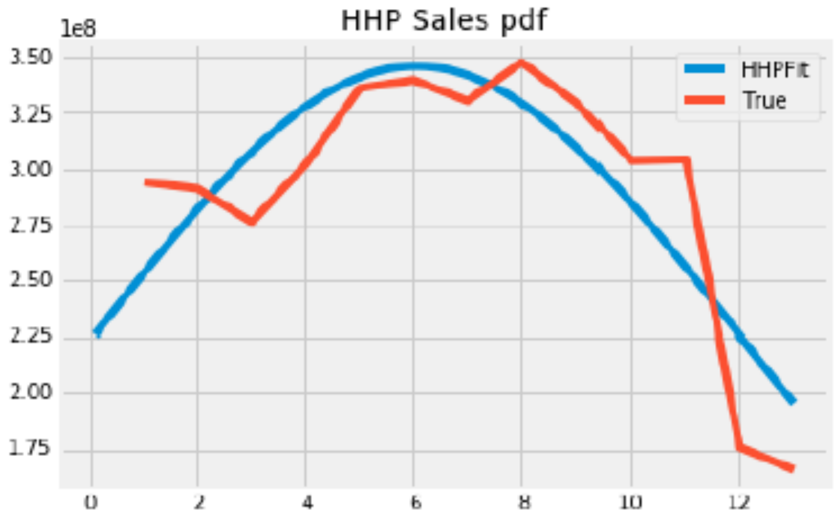
(4714514.685322818, 0.09886842320208775, 0.07252210191803433)



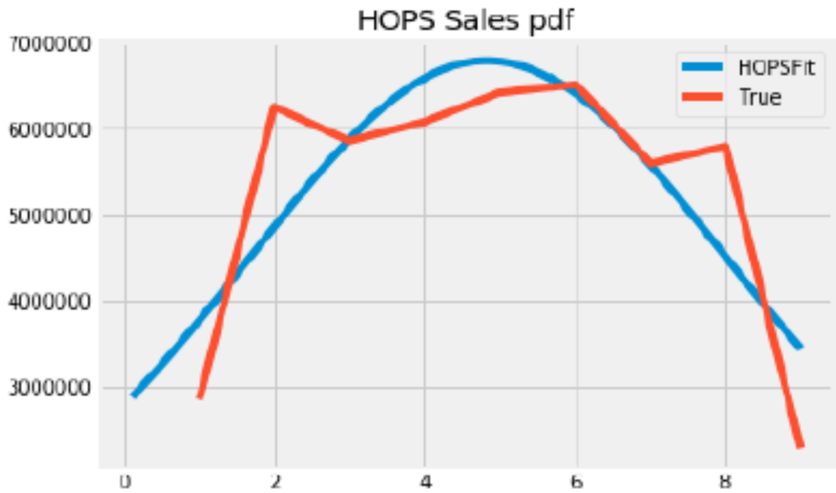
EX_S='HHP'

M, P, Q =

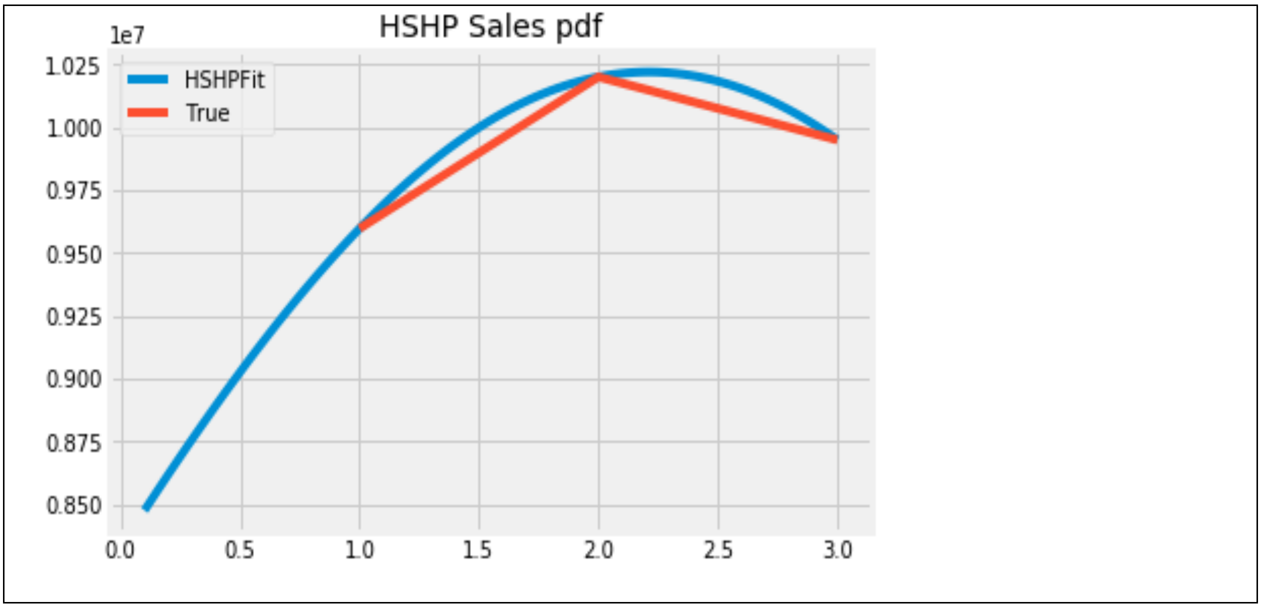
(4855388531.888743, 0.045898452764995275, 0.1815157616037806)




```
EX_S='HOPS'
M, P, Q =
(57352789.99794877, 0.048798580359637495, 0.36909588533339917)
```




```
EX_S='HSHP'
M, P, Q =
(70229071.1518704, 0.11857728283850359, 0.29770484105113076)
```


HSHP Sales pdf
1e7
1.025
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.0
0.5
1.0
1.5
2.0
2.5
3.0
HSHPFit
True

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