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WORKING PAPER

If Drywall Could Talk: A Panel Data Double Hurdle Model to Assess New Technology Adoption in the French Construction Sector

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Widespread adoption of new technologies can take time, depending on agents' perception of risk and the information they receive. It is especially true in the construction sector, yet high-performance materials are essential to ensure the efficiency and durability of the renovation and construction of dwellings. The depth of adoption is usually approached in one of two ways, either with inter-firm diffusion, which corresponds to new adoptions by firms over through time, or intra-firm diffusion, which measures the intensity of use by adopters. This paper presents an empirical procedure to estimate both dimensions simultaneously and account for geographical diffusion hubs. The estimator combines a panel data double-hurdle model and a spatial adoption index meant to capture word-of-mouth effects. A comprehensive dataset was built using scanner and geolocalized census data. The model was run using French data on an innovative gypsum board launched in 2017. Controls include both local and firm-specific features, as well as information regarding their purchase behaviors. Results suggest that inter and intra firm adoption are not driven by the same determinants, and that word-of-mouth is not the sole factor explaining the emergence of geographical clusters of adoption.

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Executive summary

This paper contributes to the literature on new technology adoption among firms, presenting an econometric model to tackle the diffusion process in two aspects: inter-firm diffusion, which corresponds to new adoptions by firms over through time, or intra-firm diffusion, which measures the intensity of use by adopters. Controls include firm-specific determinants, local market characteristics, and potential word-of-mouth are captured with an aggregated index. Estimations were run using French scanner data, exploiting the launch of an innovative gypsum board. Given the growing importance of the construction sector in the energy transition plan in France, and in most developed countries, understanding the determinants of contractors' behaviors is key to ensure regulations are effective. Their choice of materials is central to ensure the energy efficiency of both new constructions and renovated dwellings. Contrary to past contributions, this paper focuses on an innovation that is not meant to alter firms' means of production. Contractors are not the direct beneficiaries of this new product, but rather act as intermediaries: the dwelling's occupiers will ultimately be the ones deriving utility from it.

Estimation results show that (1) the characteristics of both the local market and the individual firm drive adoption, (2) only intra-firm diffusion is impacted by proximity to previous adopters, with information seemingly circulating through the stores visited and (3) store-level loyalty appears to be key determinant of the adoption process. These results also highlight the importance of accounting for intra-firm diffusion when assessing a product's market penetration, as an increasing number of first adopters does imply that more households are getting the new drywall over time. The spatial clusterization of new adoptions appears to be due to local demand specificities as well as information circulating between firms. It hints at the fact that end-client demand contributes to the inter-firm diffusion locally.

Beyond the simple regulation of dangerous and outdated products, policymakers can play a role in the diffusion of new high-performance technologies. The RGE label is the only energy-efficiency policy currently implemented that targets firms directly. It does seem to favor new adoptions, but not the intensification of usage over time. As hiring a RGE professional is a necessary requirement for households to access the main financial aid for energy retrofits, the positive impact of the label could solely indicate that reducing their financial burden allows them to ask for better products than the baseline. Its impact on intra-firm diffusion being zero or negative however indicates that new technologies are used for one-off projects, rather than a part of long-term strategies. Estimation results further suggest that material retail stores act as information hubs for firms. In practice, contractors visit them several times a week, and it is a place to meet both other contractors and specialized vendors.

A diffusion policy could thus rely on these local information hubs to spread knowledge on new products. Identifying which companies are more likely to offer state-of-the-art products to their clients and supporting their efforts is possible, but not sufficient if end-consumers are left out of the equation. Current sectoral household policies are limited to financial help for retrofits, and more focus could be put into providing them with information. Local policies could also be established to target areas where innovation uptake would be slow otherwise. It would be interesting to see if this result is specific to the Habito gypsum board, or if it holds up for other innovative products.

1 INTRODUCTION

There is a general consensus in the economic literature that technological progress is a key driving force of economic development. Less attention has however been given to the actual diffusion of innovations, that is, how production processes evolve in reaction to new technologies. Widespread adoption can take time - or even never be reached - due to the risk new means of production represent. The initial contributions by Griliches (1957) and Mansfield (1968) established that this process is far from straightforward, the latter providing ground for the S-shaped path of technology diffusion observed over time. Various papers have refined and updated these frameworks, focusing on different aspects of the process. Here, innovation diffusion is understood in two ways: inter-firm diffusion, meaning the evolution of the number of adopters over time, and intra-firm diffusion, that is, the intensity of use by adopters over time. They both contribute to the overall adoption of a new technology but are in most cases studied separately. Intra-firm adoption in particular has remained overlooked, mostly due to the lack of appropriate data. This paper aims to assess these two dimensions of technology diffusion simultaneously, as they both contribute to the success or failure of an innovation.

Understanding the determinants behind the adoption of new technologies is particularly relevant in the context of the energy transition. Green technologies allow producers and consumers to maintain their level of production or consumption while decreasing their energy use - and ultimately, their carbon footprint. This paper focuses on technical innovations impacting the housing and construction market. The residential sector accounts for a non-negligible and growing part of the energy use worldwide, reaching 26% of total final consumption among European Union countries (Eurostat 2020) and 17% in the USA (EIA 2020). Part of this consumption is due to the obsolete state of many old dwellings and could be reduced with retrofit adjustments. This is known as the "energy efficiency gap", which measures the difference between the achievable and actual energy efficiency levels. Reducing the energy use in this sector has become a key objective of current low-carbon transition plans in many developed countries. Policymakers have implemented a mix of push and pull policies, which can vary depending on national contexts, but usually take the form of subsidizing retrofits while regulating practices and materials. Construction firms' choices in terms of materials are thus central to the energy efficiency of retrofitted homes and new constructions alike. Retrofits in particular will be more effective as new and better-performing products are developed and put on the market, such as less consuming boilers, compact insulation materials, smart glass, and so on.

This paper's objective is twofold. First, it aims to provide new insights on factors of diffusion both at the inter and intra-firm levels. Second, the estimation procedure is designed to take potential word-of-mouth effects into account. In practice, it combines a panel double-hurdle model and an explicit spatial adoption index. A comprehensive dataset was built using scanner data and geolocalized census data. Controls include both local and firm-specific features, as well as information regarding firms' purchase behaviors. Estimation results can thus shine a line on the most appropriate tools for policymakers. The relative importance of firm characteristics and local market features can provide ground for national sectoral policies (eg. financial support for firms, training) or localized programs (eg. financial support for households, awareness campaings). Contrary to past contributions, this paper focuses on an innovation that is not meant to alter firms' means of production. Contractors are not the direct beneficiaries of this new product, but rather act as intermediaries: the dwelling's occupiers will ultimately be the ones deriving utility from it. As firms often guide households in their choices in terms of design and technical solutions, it is important to understand which ones are more likely to try out these new products and / or use them more than once. This is especially true in the case of renovation projects, as new building are usually constructed following a precise blueprint - firms carrying on the work do not have the leeway to choose the materials.

The following section presents a selective literature review on the adoption of new technologies by firms. The theoretical grounds for the empirical estimation are detailed in section 3 and section 4 provides insights on the dataset along with descriptive statistics. The model was run using French data on an innovative gypsum board launched in 2017. Estimation results are discussed in section 5 and Section 6 concludes.

2 Literature review

The standard theory on new technology adoption relies on two main assumptions: firms are heterogeneous in their reservation prices and economies of scale lead to a price decrease of the innovation over time. These assumptions provide ground for the diffusion path observed over time, where a simple competitive framework would lead to instantaneous widespread adoption if the innovation generates higher profits. Higher reservation prices usually stem from buyers having different risk aversion levels, as adopting new technologies come with uncertainty regarding their profitability. Firms adopt whenever it becomes profitable for them to do so, in a static or inter-temporal approach. As the price falls, an increasing number of firms expect positive profits if they adopt[1]. The initial epidemic model of diffusion developed by Mansfield (1963) predicted that firm diffusion, both inter and intra, would follow a S-shaped path. His results relied solely on the assumption that the risk associated with an innovation would decrease over time. Stoneman (1981) established a more compelling specification, using a microeconomic approach based on profit-maximizing firms and Bayesian learning to explain different adoption timings. A profitability-based approach is used in this paper to derive the empirical results, as it proved to be a better fit when estimated with real-world data (Battisti and Stoneman, 2005).

A growing body of empirical work has put these models to the test. Most papers concluded that inter-firm adoption was positively associated to firm size, either because size is assumed to be correlated to efficiency, or because bigger firms may have more leeway to try new technologies (e.g. DeCanio and Watkins 1998; Dunne 1994). Experience, usually measured by the number of years a firm has remained active on the market, was also found to increase the probability of first adoption (Zolas et al. 2021). There is no consensus on the impact of market concentration and competitive pressure: more horizontal competition increased the speed of diffusion in Karaca-Mandic, Town, and Wilcock (2017) but not in Allen, Clark, and Houde (2009) for instance. Employees' skills and R&D spending were found to have a positive effect on firms' adoption probability (Giotopoulos et al. 2017; Gómez and Vargas 2012), as well as experience with a past version of the technology (Pontikakis, Lin, and Demirbas 2006). The factors behind intra-firm diffusion have been less extensively studied, mainly due to the lack of data. Astebro (2004) focused on sunk costs, with the idea that small firms may have a harder time adjusting to a new technology. His results did support the existence of learning effects, and further implied that the choice to adopt was less plant-specific than the depth of adoption. Only plant size had an impact on the intensity of use over time, while the overall firm size had no significant effect. This result was used in this paper to define the relevant observation unit: multi-site companies are tackled at the productive unit level. The quality of human capital was also found to increase

[1] A thorough literature review on technology diffusion theory can be found in Stoneman and Battisti (2010).

firm-level demand in the case of IT technologies (Bresnahan, Brynjolfsson, and Hitt 2002). Exploring the relationship between intra-firm and inter-firm diffusion, Hollenstein (2004) found that firm size only had a significant positive effect on Internet adoption among Swiss firm up to a certain threshold. Medium-sized firms were the most likely to have an intensive usage, especially if they had had a previous experience with an older version of the technology. Likewise, Battisti, Canepa, and Stoneman (2009) showed that firm size increased the probability to adopt an e-Business technology, but had a negative impact on the intensification of usage. Intra-firm and inter-firm adoption decisions are in all cases found to be independent, and high levels of overall adoption did not lead to higher intensity of use by individual firms. For instance, Battisti and Stoneman (2003) found that limited intra-firm diffusion 30 years after the launch of a new metalworking technology was hindering the overall output produced using that technology, even though the majority of firms had adopted it.

While ICTs have been well studied in the empirical literature on the diffusion of innovation, other technologies have gotten less attention. Regarding housing more specifically, homeowners' incentives to invest in energy retrofits were found to follow the standard cost-benefits arbitrage (eg. Metcalf and Hassett 1999) and to be stronger when energy prices increased (eg. Alberini, Khymych, and Scasny 2020), but firms' motivations are less clear-cut. Yearly earnings and the size of their workforce have been associated to higher probabilities to adopt greener means of production (Gillingham, Newell, and Palmer 2009; DeCanio and Watkins 1998). Using a Swiss multi-industry firm-level survey, Arvanitis and Ley (2013) further found that competitive pressure was the strongest driver of adoption for such technologies, particularly in high energy-consuming sectors, along with factor endowment and compatibility with existing means of production. Intra-firm diffusion remained quite limited, suggesting that adopting energy-saving technologies was more likely the result of one-time investments rather than part of a wider strategy. Taxes and regulations have been found to be efficient to boost intra-firm diffusion of green technologies (Stucki and Woerter 2016). Energy-saving innovations in the construction sector also tend to target the operation stage of buildings and not their production. New products are often designed to improve the comfort of people living in buildings, not firms' profitability. As architects and contractors are the ones making the technology choices, an incentives compatibility issue can arise: the products that will maximize the occupier's utility in the long run may not be the ones maximizing contractors' profits in the short run. It may explain why new products are usually not met with a high demand right away, even those for which benefits should quickly exceed the initial cost, but there is currently little evidence on innovation diffusion among construction firms. Du et al. (2014) provided some insights using survey data on Chinese firms', finding that barriers to adoption were stronger for smaller firms, which tended to only meet the regulatory requirements. Whether these results apply to real-world product diffusion and to other contexts is still to be determined.

Finally, this paper contributes to the growing, yet sparse, literature on the spatial component of technology diffusion. Adoption by local competitors could either deter adoption or encourage it, depending on whether firms' activity is facilitated by imitation or differentiation. Distance has been found to mitigate the overall stock effect in the diffusion process, meaning that individuals or firms will be more strongly impacted by the decision of others closer to them. The concept of distance can be understood in various ways: the actual geographical distance between firms, their closeness in terms of employee education, background, area of expertise, etc. This paper uses the distance in kilometers between two firms to build a composite index, which will be discussed in Section 3. Analyses using similar methods have mainly been conducted at the international scale, and countries closer to adoption leaders were found more likely to adopt sooner and in larger proportions (Comin, Dmitriev, and Rossi-Hansberg 2012). Within-country estimations are mostly found in agricultural economics, following Case's 1992 results on the weight of adoption by neighbors to determine farmers' own propensity to adopt. This spatial effect has since been corroborated by various papers reviewing the agricultural sector in different countries (eg. Laepple et al. 2017; Ward and Pede 2015). Building on the logit estimation model with spatial dependence developed by Dubin (1995), Sarmiento and W. W. Wilson (2005) also found that spatial competition was a key driver of shuttle train elevator adoption in Nothern America. Specifically, adoption by a farmer triggered the adoption of others, but this effect decreased sharply with distance. More generally, geographical clusters of diffusion tend to appear in places where information circulates faster. ICT technologies were found to diffuse faster in regions where a lot of patents were granted (Bonaccorsi, Piscitello, and Rossi 2007) and in economically thriving areas, especially for smaller companies (Kelley and Helper 1999). Regarding intensity of usage, the overall diffusion process was estimated to be more limited in the countryside, where information spread at a slower pace (Galliano and Roux 2008). Most of the research on the construction and housing sector focused on homeowners. Their preferences were found to have a strong spatial dimension, in the sense that dwellings in socially homogeneous districts tend to display similar characteristics (Mohammadian, Haider, and Kanaroglou 2008). Energy-efficiency retrofits were undertaken more often in areas where families were younger and more educated (Morton, C. Wilson, and Anable 2018), which could lead to a faster and greater diffusion of innovative materials. The concentration of young people also seemed to stimulate the adoption of residential photovoltaic panels, with a strong impact of the adoption by close neighbors on the probability to adopt (Kim and Gim 2021). Local-level household characteristics was used in this paper to capture these potential demand-side effects on contractors' behaviors.

This paper contributes to the literature on inter and intra firm diffusion, and to the literature on the spatial component of new technology adoption. The estimation results are not fully in line with previous work, which did not account for space and time simultaneously, or only focused on one dimension of technology adoption. The estimation procedure relies on an augmented version of Cragg's double hurdle model, applied to panel data and count variables. A previous paper by Dong, Chung, and Kaiser (2004) used a similar methodology, but using a probit-normal specification while a logit-Poisson is needed here. It is also, as of writing, the first extension of Dubin's adoption index to an inter-temporal setup.

3 Model

3.1 Inter-firm diffusion

The specification of the first adoption decision takes after Dubin (1995), but has been adapted to a dynamic setup. When a new technology is introduced, firms are faced with the choice to either adopt it or keep using already existing competing products. Their decision will depend on their expected profits in case of adoption compared to their profits in case of non-adoption, denoted $\mathbb{E}(\Pi^A)$ and $\mathbb{E}(\Pi^N)$ respectively. These profits depend on a set of local building characteristics, like local temperatures or dwelling types, a set of demand-side variables such as median household revenues and dwelling prices, and a set of firm characteristics such as the number of employees and experience, all included in a matrix X. If its decisions were made independently from its rivals, a firm i located in a local market j would adopt for the first time at time t if and only if:

$$\begin{cases} \mathbb{E}_t(\Pi^A_{i,t+1}) - \mathbb{E}_t(\Pi^N_{i,t+1}) > 0 \\ \mathbb{E}_t(\Pi^A_{i,l+1}) - \mathbb{E}_t(\Pi^N_{i,l+1}) < 0 \quad \forall l < t \end{cases} \quad \text{where:} \quad \begin{cases} \mathbb{E}_t(\Pi^A_{i,t+1}) & = & f_A(X_{i,t}) \\ \mathbb{E}_t(\Pi^N_{i,t+1}) & = & f_N(X_{i,t}) \end{cases}$$

In practice, competitors' characteristics do matter, as new products may impact a firms' productivity or its differentiation strategy. More importantly, as pointed out by Sarmiento and W. W. Wilson (2005), it would be unrealistic to assume firms take strategic decisions independently from one another in such localized and competitive markets. Observing competitors' choice to adopt can either deter adoption, resulting in a Hawk-Dove or "chicken" Nash equilibrium, or on the contrary provide incentives to adopt, which leads to a dominant-strategy equilibrium. This second case generates a spatial multiplier effect, meaning the higher the number of adopters at any given time, the higher the incentives for non-adopters to switch to the new technology. The individual choice to adopt or not can hence be considered conditionally on an adoption index $AI_{i,t}$, which takes into account rival firms' adoption decisions. Their influence is mitigated with each rival's distance to firm i. Formally, denoting $d_{i,t}$ the indicator variable equal to 1 if firm i is a new adopter at time t:

$$\begin{cases} d_{i,t} = 1 \quad \text{if} \quad \begin{cases} \mathbb{E}_t(\Pi^A_{i,t+1} - \Pi^N_{i,t+1} | AI_{i,t}) > 0 \\ \mathbb{E}_t(\Pi^A_{i,l+1} - \Pi^N_{i,l+1} | AI_{i,l}) < 0 \quad \forall l < t \end{cases} \\ d_{i,t} = 0 \quad \text{otherwise} \end{cases}$$

The computation of the adoption index for each firm and each period builds on Dubin (1995) and can be understood as a weighted sum of competitors' past adoption decisions, in which distance negatively impacts the influence rivals may have on a firm i. In other words, it has a high value for firms located at the heart of diffusion hubs and a low value for firms established in places where the technology has not been tried out locally. It is meant to capture the spatial aspect of diffusion, and more precisely the existence of clusters of early adopters. Formally, denoting D_{ik} the distance in kilometers between firm i and firm k:

$$AI_{i,t} = \sum_{k \neq i} \delta_{k,t-1} \times \gamma_1 \times \exp\left(\frac{-D_{ik}}{\gamma_2}\right) \quad \text{where} \quad \delta_{k,t-1} = \sum_{l=0}^{t-1} d_{k,l}$$

A firm k's former adopter status in period t is given by $\delta_{k,t-1}$, which is equal to one if they have adopted prior to t. The factor γ_1 captures the overall impact of neighboring firms' decision on that of a company's choice to adopt or not. The term γ_2 captures the rate at which this influence decreases with distance. Since $\lim_{\gamma_2 \to \infty} \exp\left(\frac{-D_{ik}}{\gamma_2}\right) = 1$, a high γ_2 would indicate that distance does not matter, meaning only the overall number of adopters affects a firm's decision. If both terms are found to be jointly insignificant, it would indicate that there is no spatial effect and that only the local and firm-specific characteristics matter in the adoption process.

In this setup, firms' individual decisions are assumed to be driven by the difference in their expected profits, denoted $\Pi^*_{i,t} = \mathbb{E}_t(\Pi^A_{i,t+1} - \Pi^N_{i,t+1} | AI_{i,t})$. These profits are unobservable in the data used for the estimations, as it only provides purchase information. It is thus further assumed that purchase decisions are the result of latent profit maximization and that the latent variable $\Pi^*_{i,t}$ depends on the controls $X_{i,t}$, on the adoption index $AI_{i,t}$ and on an individual and time-specific component $u_{i,t}$:

$$\Pi^*_{i,t} = X_{i,t}\alpha + AI_{i,t} + u_{i,t}$$

The error terms $u_{i,t}$ are assumed to be independent, meaning that the spatial interaction is fully captured by the adoption index. Assuming $u_{i,t}$ follows a logistic distribution, the probability of adoption is given by:

$$\begin{aligned}
\mathbb{P}(d_{i,t}=1) &= \mathbb{P}(\Pi^*_{i,t}>0) \times \textstyle\prod_{l=0}^{t-1} \mathbb{P}(\Pi^*_{i,l}<0) \\
&= \left(1-\mathbb{P}(u_{i,t} < -(X_{i,t}\alpha + AI_{i,t}))\right) \times \textstyle\prod_{l=0}^{t-1} \mathbb{P}(u_{i,l} < -(X_{i,l}\alpha + AI_{i,l})) \\
&= \frac{\exp\left(X_{i,t}\alpha + AI_{i,t}\right)}{1+\exp\left(X_{i,t}\alpha + AI_{i,t}\right)} \times \frac{1}{\prod_{l=0}^{t-1}\left(1+\exp(X_{i,l}\alpha + AI_{i,l})\right)} \\
&= \frac{\exp\left(X_{i,t}\alpha + AI_{i,t}\right)}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha + AI_{i,l})\right)}
\end{aligned}$$

The maximum likelihood estimator is then found by summing the following log-likelihood function over time[2]:

$$\begin{aligned}
\ln(L_t) &= \textstyle\sum_{i\in N}\left(d_{i,t} \times \ln\left(\frac{\exp\left(X_{i,t}\alpha+AI_{i,t}\right)}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)}\right) + (1-d_{i,t}) \times \ln\left(\frac{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right) - \exp\left(X_{i,t}\alpha+AI_{i,t}\right)}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)}\right)\right) \\
&= \textstyle\sum_{i\in N}\left(d_{i,t} \times \ln\left(\frac{\exp(X_{i,t}\alpha+AI_{i,t})}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right) - \exp(X_{i,t}\alpha+AI_{i,t})}\right) + \ln\left(\frac{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right) - \exp\left(X_{i,t}\alpha+AI_{i,t}\right)}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)}\right)\right)
\end{aligned}$$

3.2 Intra-firm diffusion

Inter-firm adoption is not sufficient to capture the overall adoption diffusion process. The panel structure of the data can be exploited to assess the intensity of use by adopters over time. Firms are assumed to make sequential choices, deciding first whether or not to adopt, and then the optimal quantity to purchase. It can be modeled following a double hurdle approach, originally developed by Cragg (1971) to estimate the demand for durable goods. This two-part model is more flexible than the Heckman framework as it allows null observations in the second stage. It is essential in the case of intra-firm diffusion since adopters may not repeat purchase, but that does not make them non-adopters. The first stage is estimated on the overall population based on the extended Dubin model described previously.

The second hurdle aims to determine the extent of adoption by specifying an outcome equation that will be estimated only among adopters. The observed quantity bought by a firm, denoted $q_{i,t}$, is assumed to be dependent on their current and past decisions to adopt, and the optimal quantity maximizing their profits, denoted $q^*_{i,t}$ - which is again an unobserved latent variable. Formally:

$$\begin{cases} q_{i,t} = q^*_{i,t} \quad \text{if} \quad q^*_{i,t} > 0 \quad \text{and} \quad \exists l \leq t \quad \text{such that} \quad \Pi^*_{i,l} > 0 \\ q_{i,t} = 0 \quad \text{otherwise} \end{cases}$$

Ultimately, the observed variable at each time t and for each firm i is $q_{i,t} = \delta_{i,t} \times q^*_{i,t}$. Following the extension

[2] Estimation methods are described more extensively in Honoré and Kyriazidou (2000).

of double hurdle models by Greene (1994), it is assumed that $q^*_{i,t}$ follows a Poisson distribution[3]. Assuming both hurdles are independent and denoting f the Poisson distribution function, we find:

$$\begin{array}{rcl}
\mathbb{P}(q_{i,t}=0) & = & \mathbb{P}(\delta_{i,t}=0)+\mathbb{P}(\delta_{i,t}=1; q^*_{it}=0) \\
& = & \prod_{l=0}^{t}\mathbb{P}(\Pi^*<0)+\left(1-\prod_{l=0}^{t}\mathbb{P}(\Pi^*<0)\right)\times f_t(0) \\
& = & \frac{1}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)}+f_t(0)\times\frac{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)-1}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)} \\
\mathbb{P}(q_{i,t}=k) & = & \mathbb{P}(\delta_{i,t}=1; q^*_{it}=k) \quad \forall k\in\mathbb{N}^* \\
& = & \left(1-\prod_{l=0}^{t}\mathbb{P}(\Pi^*_{i,l}<0)\right)\times f_t(k) \quad \forall k\in\mathbb{N}^* \\
& = & f_t(k)\times\frac{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)-1}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)} \quad \forall k\in\mathbb{N}^*
\end{array}$$

It is then straightforward to show that the probability density function of the observed variable $q_{i,t}$ is given by:

$$\begin{array}{rcl}
\mathbb{P}(q_{i,t}=k) & = & f_t(q_{i,t})\times\frac{\prod_{l=0}^{t-1}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)-1}{\prod_{l=0}^{t-1}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)}+\frac{1}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)}\times\mathbb{1}_{q_{i,t}=0} \\
& = & \frac{\exp\left(-\lambda_{i,t}\right)\times\left(\lambda_{i,t}\right)^{q_{i,t}}}{\left(q_{i,t}\right)!}\times\frac{\prod_{l=0}^{t-1}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)-1}{\prod_{l=0}^{t-1}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)}+\frac{1}{\prod_{l=0}^{t}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)}\times\mathbb{1}_{q_{i,t}=0}
\end{array}$$

$$\text{where:}\quad \begin{cases} k\in\mathbb{N} \\ \mathbb{1}_{q_{i,t}=0}=1 \quad \text{if} \quad q_{i,t}=0; \quad 0 \quad \text{otherwise.} \\ \lambda_{i,t}=\exp\left(X_{i,t}\beta\right) \end{cases}$$

The parameters can be estimated by maximizing the sum of the following log-likelihood function over time, where $N_t \subset N$ is the subset of adopters at time t[4]:

$$\begin{array}{rcl}
\ln(L_t) & = & \sum_{i\in N_{t+1}}\ln\left(\mathbb{P}(q_{i,t}=k)\right) \\
& = & \sum_{i\in N_{t+1}}\ln\left(\frac{\exp\left(-\exp(X_{i,t}\beta)\right)\times\left(\exp(X_{i,t}\beta)\right)^{q_{i,t}}\times\prod_{l=0}^{t-1}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)-1+\mathbb{1}_{q_{i,t}=0}\times\left(q_{i,t}\right)!}{\left(q_{i,t}\right)!\times\prod_{l=0}^{t-1}\left(1+\exp(X_{i,l}\alpha+AI_{i,l})\right)}\right)
\end{array}$$

4 Data

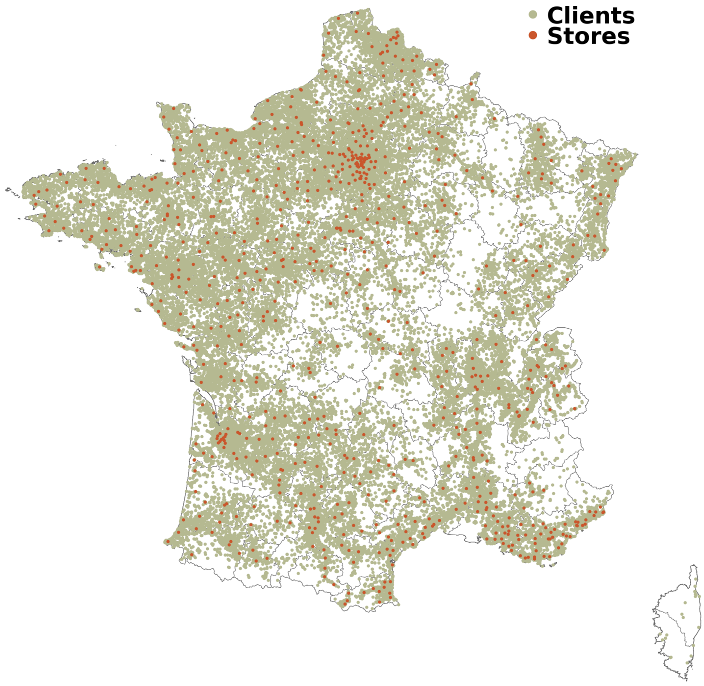
4.1 Sales data and firms' characteristics

The model is applied to the diffusion of the Habito gypsum board, using sales data from one of the largest material retailer targeting professionals on the French market. They cover all subgroups of the construction activity, from masonry to plumbing or woodwork, and they have stores all over the metropolitan territory. Figure 1 displays the locations of the stores and their clients. They are not homogeneously distributed across the territory, as they are relatively more present in the South-West and less so in the North-East. Nevertheless, this dataset provides a dense coverage of construction firms in France. The Habito drywall was launched by the manufacturer Placo in January 2017 and has two major innovative characteristics. First, it is much

[3]The original formulation by Cragg assumes the error terms of the two hurdles follow a normal distribution, while we follow a Logit-Poisson procedure.

[4]Computations of first and second derivatives can be found in Greene (1994).

stronger than standard gypsum boards[5], which can only hold up to 30 kg with anchors and 5 kg without, versus 60 kg and 20 kg for Habito. It also implies less breakage during transportation and a higher resistance to shocks, making for more durable buildings. Second, this board facilitates the installation of insulation underneath, for instance with vacuum insulation panels or using Isover's "Optimax mounting system". The latter is particularly interesting, as it both reinforces the energy efficiency of the wall by avoiding thermal bridges, and limits waste on the work site by suppressing 80% of the metal framing necessary to mount traditional drywall. From the contractor's perspective, it also means a faster and cleaner installation, as it reduces repetitive tasks like screw-driving and steel cutting. As drywall boards come in various dimensions, the quantity purchased was transformed into square meters - for instance a board of height 2.5m and width 1.2 is equivalent to $3m^2$.



Source: Author computations.

Figure 1: Locations of stores and clients

Compared to previous work on diffusion, this dataset contains information on several years of material purchases by the same construction firms, hence the diffusion process is directly tractable. Since it is not an *ad hoc* survey, the usual non-respondent bias also isn't an issue. The initial data was restricted to stores from which an Habito board was purchased at least once, and to firms that purchased a standard BA-13 drywall board at least once over the four-year period and for which all information was available. The final sample contains roughly 20 000 firms for each year, which totals to 77 860 observations over the four years. At first glance, intra-firm diffusion appears quite low (Figure 2). There is a sharp decrease in the average quantity

[5]Placo BA13 drywall is used as the baseline product.

bought and the median is at zero for all years after the first adoption. There is however a stronger uptake at $t+3$, suggesting some firms did repeat their purchase in the long run.

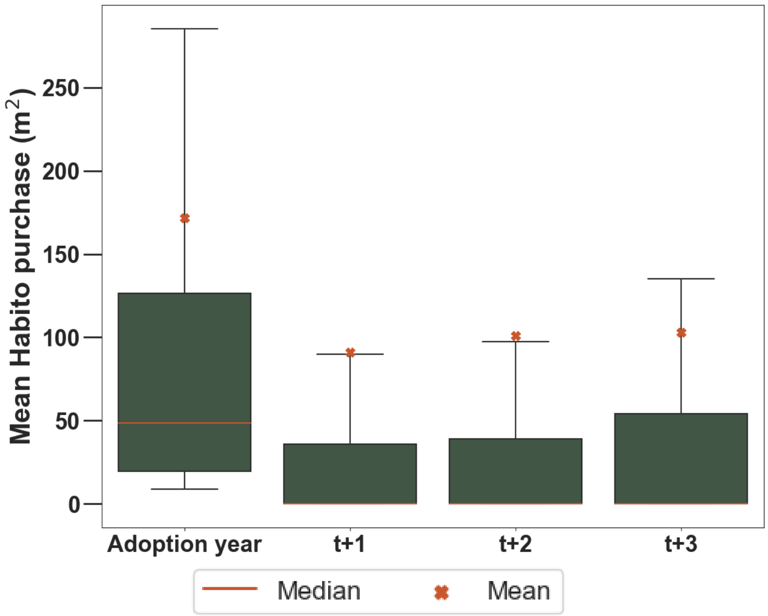


Figure 2: Quantity bought at and after adoption

Source: Author computations.
Note: Adoption year corresponds to year t; group size varies for each t. Typically contractors who first adopted in 2017 appear in all four groups, while those who first-adopted in 2018 cannot appear in the "$t+3$" category.

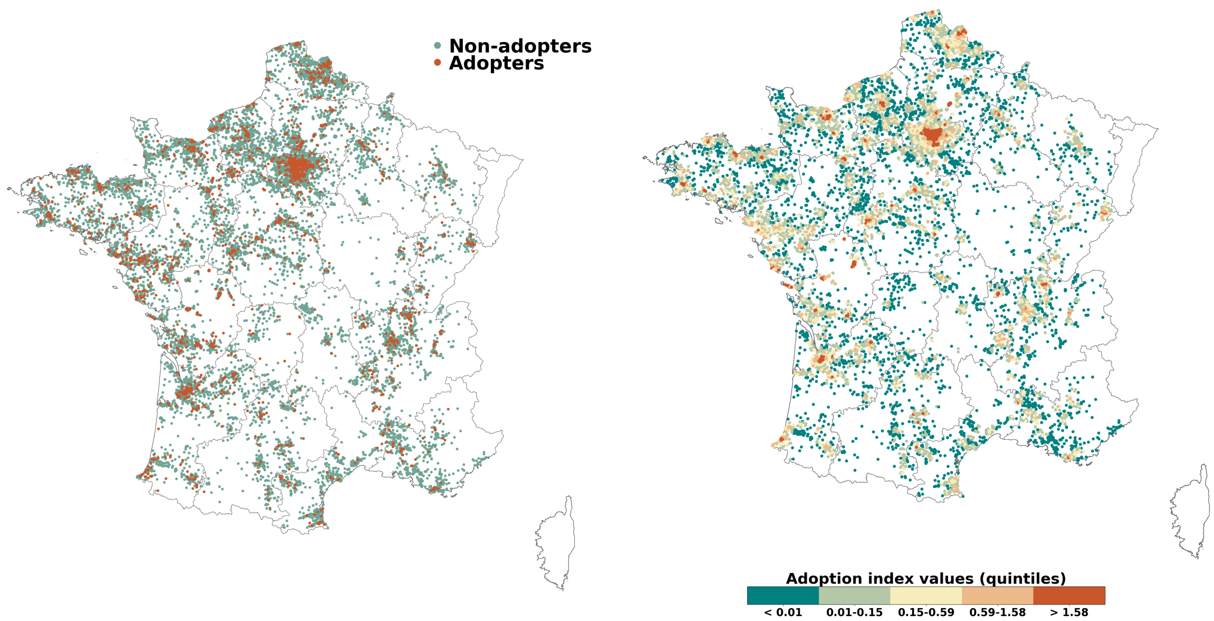


Figure 3: Adopters' locations (left) and individual adoption index values for $\gamma_2 = 1.7$ (right)

Source: Author computations.
Note: The adoption index displayed is the result of the likelihood maximization further detailed in Section 5, meaning $\gamma_2 = 1.7$

Firms' professional id (SIRET) was used to merge administrative information on each firm, such as their number of employees and the date of their creation, found in the SIRENE dataset produced by the French National Institute of Statistics and Economic Studies (Insee). Using their addresses, firms have been associated to GPS coordinates using the application programming interface of the "National Address Database" (BAN), also produced by the Insee. The adoption index for each firm was computed using these GPS coordinates. It seems to capture the spatial aspect of diffusion fairly well (Figure 3) - the figure displays the 2020 values but the correlation holds throughout the period. Diffusion hubs appear quite clearly, mostly located in the North. Some of them are linked to urban concentration, like around the cities of Paris, Lyon or Lille, which is expected. Cities have more economic activity and information tends to spread faster. More surprisingly, adopters also ended up concentrated in sparser places, notably along the North-Western coast, hinting that urban density is not the only factor driving the emergence of adoption clusters.

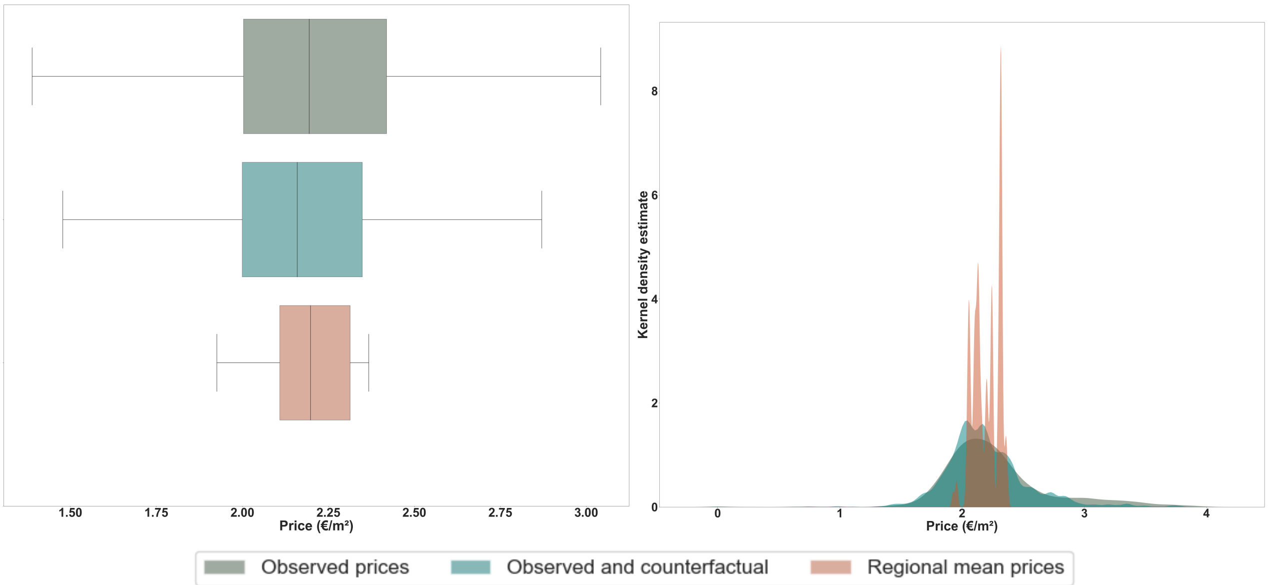


Figure 4: Observed and counterfactual prices

Source: Author computations.
Note: The boxplots on the left display the median and the inter-quartile range, as well as the minimum and maximum values. Counterfactual prices for non-purchasers correspond to the store average. Leave-one-out mean prices were obtained for each firm j in sales-region s by averaging the price on the whole region excluding j. Formally, denoting J_s the number of firms in region s and P_k the price (observed or counterfactual) associated to each firm k in region s, the leave-one-mean for firm j is given by: $\sum_{k \neq j} \frac{P_k}{J_s - 1}$.

Prices were left out of the analysis due to data inconsistency. Since adoption was low overall, the actual purchase price was available for roughly 14% of firms, for which there was at least one observation - in total, only 6% of the panel observations contained an observed price. Using the store average as a counterfactual price for non-purchasers has been considered, since it did not drastically decrease price variation and seemed to be a good fit for the observed price distribution (Figure 4). The real issue arised when dealing with price endogeneity. The retailers' stores being divided into 11 "sales regions" in terms of logistics and suppliers, aggregated leave-one-out mean prices could have been used to instrument retail prices. Since most observations consisted in counterfactual store-level prices, there was very little variation left in the leave one-out mean prices (Figure 4, left). Further, even though the median is similar, their overall distribution did not match the observed and counterfactual prices' (Figure 4, right). First-stage results were thus not compelling and prices were removed from the regressors, which prevented the estimation of price elasticities. In practice, prices are negotiated on a one-to-one basis with clients, which means that purchase prices are in fact dependent on each firm's characteristics. As such, the impact of firm determinants on adoption will provide some information on the effect of price - typically, larger firms and regular clients are offered lower resale prices.

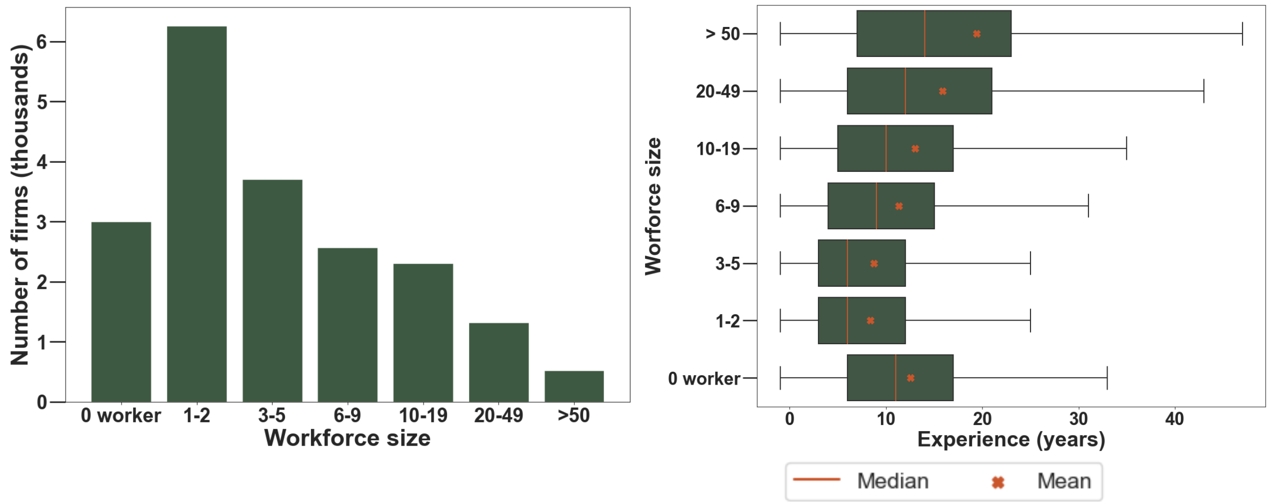


Figure 5: Workforce size and experience

Source: Author computations from Insee data.
Note: Workforce size refers to the number of employees. Years of experience correspond to 2020 values.

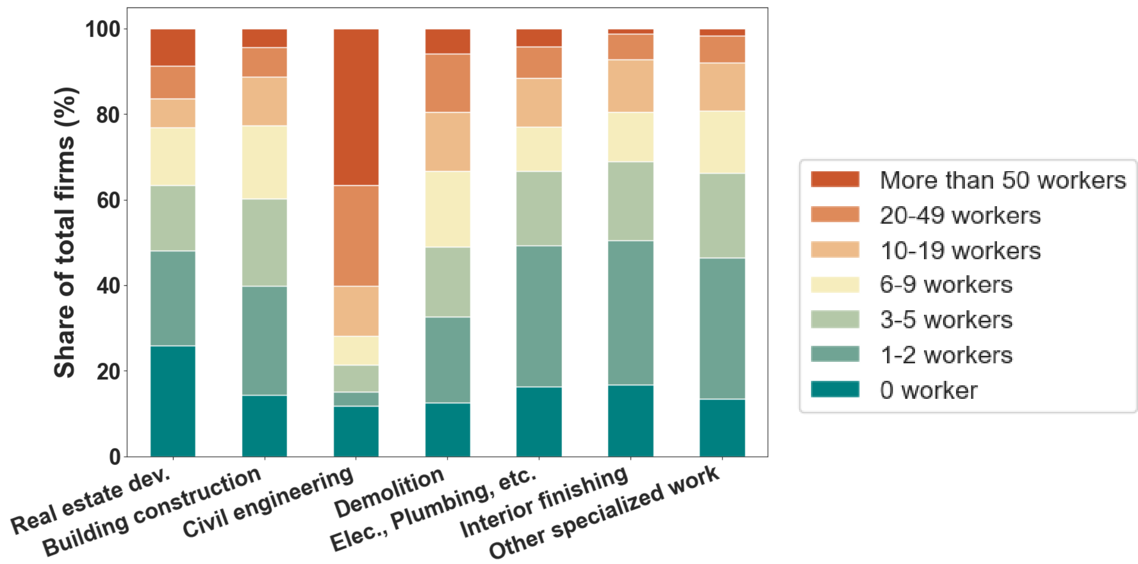


Figure 6: Firms' professional trades

Sources: Author computation from Insee data.
Note: Shares correspond to 2020 values.

Very small companies are slightly under-represented in our final sample compared to their importance among French construction firms as a whole (Figure 5, left). They still account for a large part of the sample, as 47% of firms have less than two employees. Figure 5 (right) displays the average, mean and quantiles of the number of years of experience per workforce size categories. It is interesting to note that workforce size does not linearly increase with experience, measured by the number of years during which a firm has been active on the market. In particular, a number of seasoned professionals have kept their productive structures small, having no employees, which matches figures on the overall market. Construction firms also differ with respect to their professional trades, meaning the nature of their activity (Figure 6). The seven categories used in this paper correspond to Insee intermediate categories for construction firms. The distribution of companies with respect to their size is comparable across categories, except Demolition and Civil Engineering, in which there is a majority of larger firms. The reference category used in the estimations is interior finishing, which contains trades which are expected to use the largest amounts of gypsum boards: drywallers, carpenters, plasterers, etc.

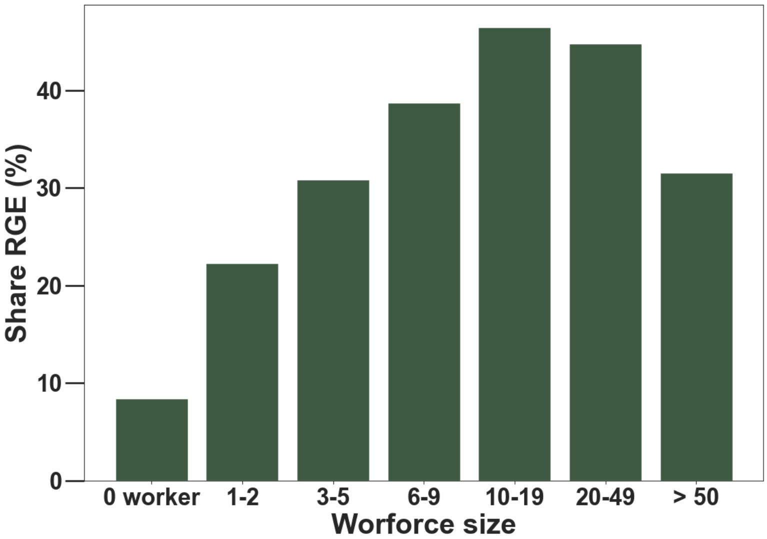


Figure 7: RGE label

Source: Author computations from ADEME data.
Note: Workforce size refers to the number of employees. Shares of RGE firms correspond to 2020 values.

Additional information on the "*Reconnu Garant de l'Environnement*" (RGE)[6] certification was included. It is a costly label construction companies can obtain following a training program and an audit of the quality of their work. As energy retrofit tax rebates for homeowners are conditional on their contractor having the RGE label, skilled contractors have a high incentive to obtain the certification in order not to lose customers. Firms getting the label are then constrained to use products from a list of environmentally friendly materials defined at the State level, which contains Habito. The RGE label may also reveal a company's inclination towards more durable and sustainable practices. Information on labels was found in the "RGE historical dataset", published by the French Agency for the Environment and Energy Management (ADEME), which provides the precise time intervals during which a firm was labeled. These intervals were used to determine how many months each firm has been labeled for since January 2017 - normalized at 0 for firms that were never labeled. On the final sample 63.4% of firms never got the label and more than 90% of companies which got the RGE label at least once have less than 20 employees, which is consistent with the figures found at the national scale (Belin and Lefort 2017). There is a however higher proportion of labelled firms among larger companies, namely with more than 10 employees (Figure 7).

[6] "*Reconnu Garant de l'Environnement*" can be translated to "Recognised Environmental Guarantor".

4.2 Local characteristics

Firms' locations were also used to cross the sales data with city-level information. Regarding households, who are contractors' end-clients, the French census provides information on the number of dwellings, the share of owners and on the share of houses among dwellings (Figure 8). These variables capture how local demand may drive or deter new technology adoption. In particular, owner-occupiers are known be more prone to renovating their dwellings than people who rent out their properties. The same goes for people living in houses, since collective living poses coordination challenges when considering home improvements. Both shares are largely above 50% on the metropolitan territory, meaning owner-occupied individual houses are the norm, but there are some disparities. They also appear quite correlated, except in city centers where there collective living is the norm, but the share of owner-occupiers remains high.

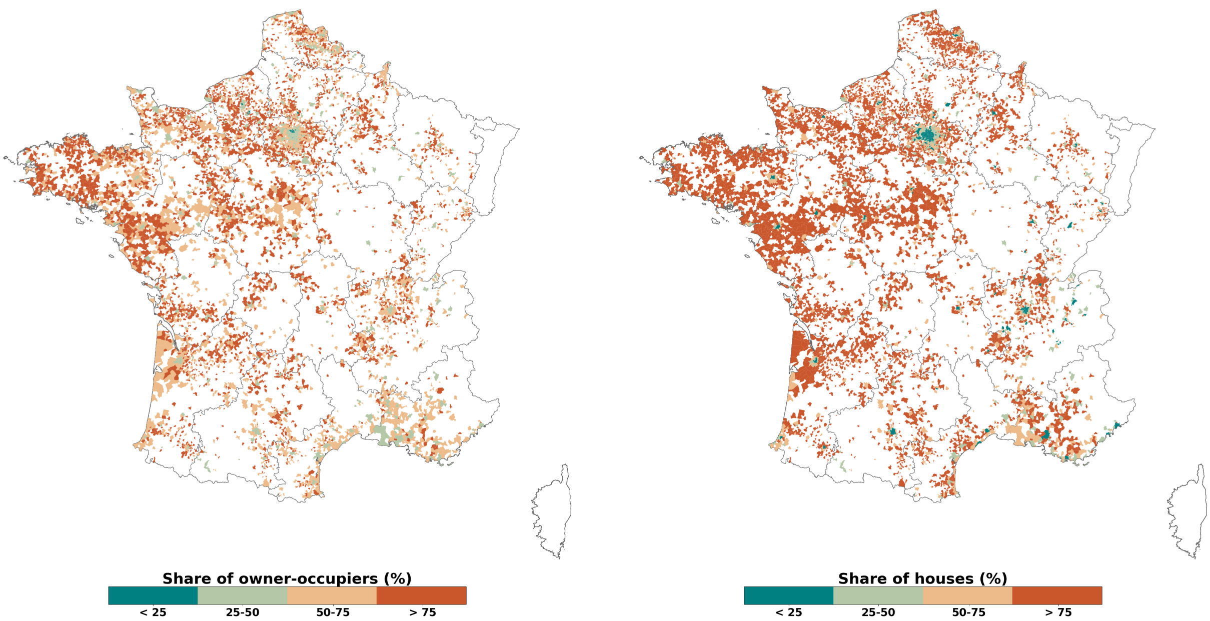


Figure 8: Local shares of owner-occupiers (left) and houses (right)
Source: Author's computations from Insee data.
Note: The local share of homeowners is computed among all resident households in the area; the share of houses is computed among the total number of dwellings in the area.

Information on households' incomes is not directly found in the census. The Insee releases the "Localized disposable income system" (Filosofi) database every year, which contains tax data aggregated at the city level. It contains inforamation on median standards of living, which were used as a proxy for households' purchasing power. Local characteristics also include heat sensitivity measures made available by the French electricity distributor ENEDIS, computed using the share of energy consumption due to temperature variations below or above reference temperatures for the area. The national average heat-sensitive consumption is 2400 MW (RTE 2019), but there is evidence of North-South heterogeneity due to local climate differences. Property prices per square meters were found in the "*Demandes de valeurs foncières*" (DVF)[7] database, produced yearly by the French Treasury using information on real-estate transactions. Finally, local average blue-collar wages were drawn from the Insee "*Base Tous Salariés*" (BTS)[8] dataset to account for firms' labor costs (Figure 9,

[7] It can be translated to "Property value requests".
[8] "All Employees Database".

left). There are some local variations in wages, but the difference between extreme values is not extremely drastic due to the inertia of the minimum wage in France. Firms' competitive environment is proxied using the number of construction firms in their town. (Figure 9, right). Competitive pressure appears particularly high along the West coast, as well as in the three major cities - Paris, Lyon and Marseille.

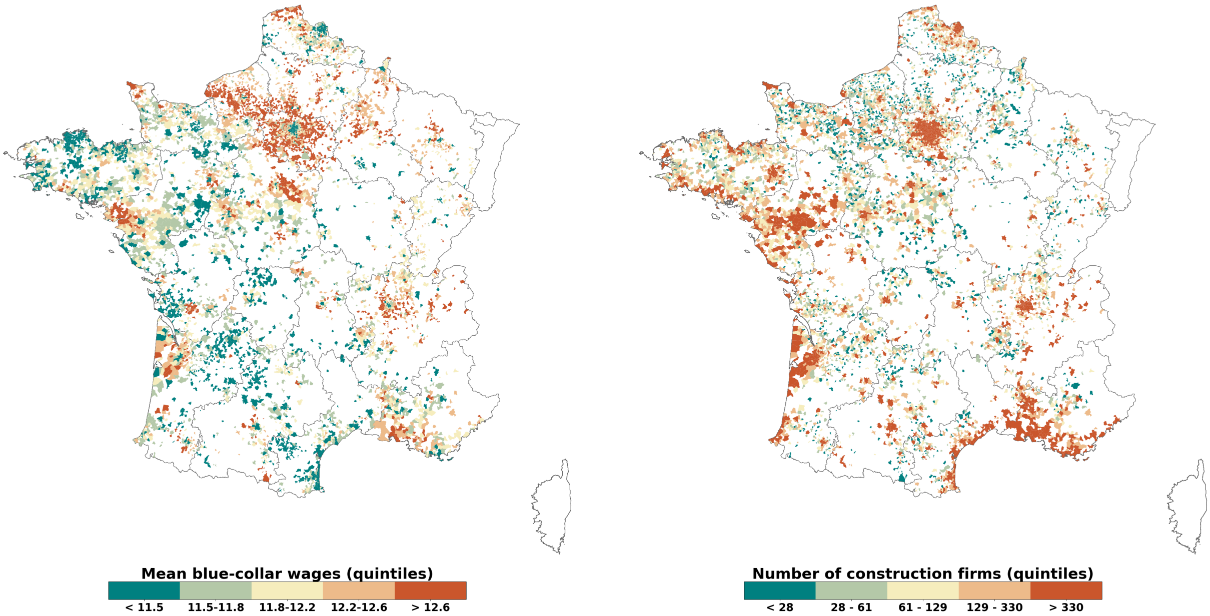


Figure 9: Firms' economic environment

Source: Author's computations from Insee data.
Note: 2020 values; blue collar wages correspond to locally aggregated average net salaries, expressed in € per hour. Competition is proxied by the number of construction firms in the same city.

5 Empirical estimation

5.1 Main results

An overview of the main variables is provided in Table 1. Regression results are presented in Table 2, with specification (1) presenting a baseline regression without the adoption index. Coefficients in specification (2) were obtained by running the same model for different values of γ_2 in order to find $\gamma = (\gamma_1, \gamma_2)$ that best fits the data. This grid search process was conducted by increasing γ_2 by 0.1 from 0.1 to 10. The resulting γ_1, which measures the average impact adjacent firms have on one another, is significantly negative only in the second hurdle. It means that other firms do not impact new adoption decision, which hints at the fact that their own clients would be the ones asking for Habito drywall. It also hints at a positive word-of-mouth effect, meaning the proximity to previous adopters increases the intensity of use. The corresponding value for γ_2, that can be interpreted as the rate at which adjacent firms' impact diminishes, is however quite high. In other words, adoption by others would tend to undermine the quantity a firm may purchase, even though this influence decreases sharply when distance increases. Policy-wise, RGE contractors have a higher probability of adoption but tend to purchase less than their non-labeled counterparts. The higher first adoption probability is consistent with the restrictions on materials imposed by the label, which aim to favor new technologies, and hence boost first adoptions. This is also consistent with the idea that firms choosing the certification are more prone to innovate, and would thus be part of the early adopters. The negative effect on quantity could however hint that the Habito drywall did not meet their expectations and they went back to the baseline product after their first purchase.

Variable	Mean	Standard deviation	Max	Min
Adoption	0.08	0.27	1.00	0.00
Habito drywall (m^2)	6.15	109.24	13063.68	0.00
Standard drywall (m^2)	861.35	4675.38	256381.27	0.00
Purchase frequency (%)	7.06	14.69	210.00	0.00
Normalized Herfindahl index	0.48	0.48	1.00	0.00
Head office	0.88	0.33	1.00	0.00
Experience	10.83	11.31	120.00	0.00
RGE	0.32	0.47	1.00	0.00
Property prices	16681.80	97083.59	3904886.50	0.01
Competition	1802.59	4122.88	44614.00	1.00
Sh. heat-sensitive (%)	26.93	7.78	85.87	1.84
Dwellings	12034.52	23957.20	253061.88	15.00
Sh. owners (%)	62.31	17.63	98.16	14.96
Sh. houses (%)	66.03	29.92	100.00	0.32
Med. disp. income	21947.77	3870.85	46280.00	13025.77
$\mathbb{1}_{>30\text{m}^2}$	0.84	0.37	1.00	0.00
Blue collar wages (€)	11.53	0.77	19.04	8.44

Values are computed on the entire panel.

Table 1: Summary statistics for non-categorical variables

Scanner data offers the possibility to control for contractors' purchasing behaviors beyond adoption. The quantity of baseline product purchased has a significantly positive effect on both adoption and quantity. Adopters seem to purchase large quantities of Placo drywall in general, meaning they are familiar with the standard BA13. An indicator equal to one if more than 30m^2 of drywall - Habito or standard - was purchased and zero otherwise was also included in the regressors and has a significantly positive coefficient. The purpose of $\mathbb{1}_{>30\text{m}^2}$ is to indicate whether a contractor has purchased enough drywall over the year to complete at least one room. As there is no definition of a "standard" room in the industry, the minimal wall surface of a livable room was derived from two norms. First, the minimum livable surface was set at 9m^2 by the 1996 Carrez law in France. Second, standard new construction usually come with 2.5 meter high ceilings. With these two constraints, the minimum amount of drywall necessary for a room, denoted $S_{\min}$, is obtained by solving the following program:

$$\begin{cases} \min_{(l,L)} & S = 2 \times 2.5 \times \left(l + L\right) \\ \text{s.t.} & l \times L = 9 \end{cases} \iff \min_{L} \quad 5\left(L + \frac{9}{L}\right) \iff \begin{cases} l_{\min} = L_{\min} = 3\text{m} \\ S_{\min} = 30\text{m}^2 \end{cases}$$

It corresponds to ten 2.5 × 1.2 drywall boards, which are the most commonly found. The frequency of purchase, measured in percentages of business days[9] also has a positive impact. The earliest adopters appear to be recurrent clients, who use large quantities of drywall in their day-to-day activity. Habito demand is also driven by firms with higher purchasing concentration. In other words, loyalty to a store appears to boost a firm's early demand for the new product. This is captured by a normalized Herfindahl Index (HI), which was computed for each firm i using $M_{i,t}$ the number of store they visited at time t and the share of their annual expense each store m represents, denoted $s_{i,t,m}$:

[9]Business days exclude week-ends, bank holidays and confinement periods for each given year.

	(1)		(2)	
	Adoption	Quantity	Adoption	Quantity
Standard drywall (m^2)	0.000006**	0.000001	0.000006**	0.0000001
	(0.000002)	(0.000012)	(0.000002)	(0.000000)
Purchase frequency (%)	0.047449***	0.054201***	0.047388***	0.055940***
	(0.002711)	(0.017781)	(0.002710)	(0.000393)
Normalized Herfindahl index	0.025991	0.621706**	0.026132	0.636920***
	(0.021647)	(0.313308)	(0.021720)	(0.009880)
Reference category: No employee				
1-2 workers	0.009202	-0.309367	0.007952	-0.446582***
	(0.082843)	(0.273580)	(0.082843)	(0.137640)
3-5 workers	0.039306	0.077695	0.037701	-0.060733
	(0.088898)	(0.327277)	(0.088818)	(0.149325)
6-9 workers	0.116966	0.482829	0.116025	0.293148*
	(0.093786)	(0.306610)	(0.093751)	(0.152346)
10-19 workers	-0.088349	0.370974	-0.089693	0.322290**
	(0.099724)	(0.260987)	(0.099745)	(0.156148)
20-49 workers	-0.076945	1.207289	-0.077785	1.535955***
	(0.118947)	(0.747164)	(0.118847)	(0.217272)
> 50 workers	-0.035915	1.123403	-0.034692	1.617938***
	(0.176238)	(0.764231)	(0.176387)	(0.282006)
Reference category: Interior finishing				
Real estate dev.	0.388580	-0.386473	0.391152	-0.504311
	(0.239652)	(0.314850)	(0.239193)	(0.385341)
Civil engineering	-0.225610	0.844597	-0.223331	1.142316*
	(0.383055)	(0.878428)	(0.383021)	(0.587689)
Building construction	-0.114839	0.588642	-0.117193	0.554685***
	(0.077755)	(0.427084)	(0.077873)	(0.127169)
Demolition	-0.949931**	0.271231	-0.949097**	0.303376
	(0.378750)	(0.674879)	(0.378761)	(0.584897)
Elec., plumbing, etc.	-0.364626***	0.451476	-0.366216***	0.455013***
	(0.084934)	(0.307287)	(0.085004)	(0.135869)
Other specialized work	-0.254892***	0.224063	-0.255314***	0.372861***
	(0.061650)	(0.281206)	(0.061641)	(0.099415)
Head office	-0.112077	0.056594	-0.112595	0.106089
	(0.077211)	(0.206807)	(0.077204)	(0.127620)
Experience	-0.001837	-0.024566	-0.001922	-0.039643***
	(0.002413)	(0.028683)	(0.002421)	(0.002317)
RGE	0.228688***	-0.310818	0.229771***	-0.304792***
	(0.053064)	(0.279946)	(0.053076)	(0.009914)
Property prices	-0.000001	0.000001	-0.000001	0.000001***
	(0.000000)	(0.000001)	(0.000000)	(0.000000)
Competition	-0.000003	0.000321	-0.000004	0.000629***
	(0.000016)	(0.000316)	(0.000017)	(0.000019)
Sh. heat-sensitive (%)	-0.006601*	0.012346	-0.005696	0.014790***
	(0.003559)	(0.019203)	(0.003702)	(0.000627)
Dwellings	0.000001	-0.000042	0.000001	-0.000078***
	(0.000003)	(0.000038)	(0.000003)	(0.000003)
Sh. owners (%)	-0.007691**	0.085035	-0.007299*	0.087817***
	(0.003726)	(0.053613)	(0.003750)	(0.004864)
Sh. houses (%)	0.008741***	-0.044588	0.008830***	-0.042992***
	(0.002237)	(0.030377)	(0.002245)	(0.003322)
Med. disp. income	0.000016*	-0.000211	0.000015	-0.000237***
	(0.000010)	(0.000155)	(0.000010)	(0.000006)
Blue collar wages (€)	-0.069966*	-0.156580	-0.071990*	-0.149725***
	(0.039420)	(0.351155)	(0.039576)	(0.012619)
$\mathbb{1}_{>30\text{m}^2}$	2.334214***	3.340316***	2.332834***	3.346774***
	(0.100563)	(0.237066)	(0.100596)	(0.034476)
γ_1			0.038862	0.306033***
			(0.039482)	(0.008723)
Observations	80,240	3,854	80,240	3,854
Groups	21,590	1,642	21,590	1,642
γ_2			1.5	10
Robust s.e.	Yes	Yes	Yes	Yes

Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2: Main results

$$HI_{i,t} = \begin{cases} \frac{\sum_{m=1}^{M_{i,t}} s_{i,t,m}^2 - 1}{1 - \frac{1}{M_{i,t}}} & \text{if } M_{i,t} > 1 \\ 1 & \text{if } M_{i,t} = 1 \end{cases}$$

Specific trades were also included as a categorical variable. The reference category in the regression is interior finishing, which includes professionals who are expected to use drywall: carpenters, drywallers, plasterers, etc. It is interesting to note that professionals in plumbing and electricity, as well as contractors specialized in new constructions, have a lower probability of adoption but tend to buy larger quantities when they do. For the former, it can be linked to the nature of their activity, as they work more often in kitchens and bathroom where heavy furniture is often suspended on the walls. It is possible that there are higher returns to adoption for these contractors. For the latter, it can be due to the scale of their projects - contrary to renovation projects, they are in charge of entire houses or apartment buildings. As both are however not specialized on plaster boards, they are not the earliest adopters. The size of the firm in terms of employees does not seem to impact adoption, but does positively affect the total quantity purchased, which can be related to the scale of the activity. It is consistent with the effect of the years of experience. Overall, the nature of the activity seems to impact adoption - interior finishing specialists have a relatively higher chance to adopt -, but the scale of their business seem to drive the quantity used.

Ultimately, drywall is only an intermediate input, purchased by a contractor to meet their client's needs. It is hence important to account for local market characteristics. Property prices in the city where the firm is located have an ambiguous effect, having no effect on the probability of adoption but positively impacting the quantity. Higher prices however can indicate the presence of households with a higher willingness to pay for housing, hence the positive coefficient on the quantity bought after adoption. The share of houses also has a positive impact on the probability to adopt but not on quantity, maybe reflecting again that the Habito drywall is only used in specific areas of a dwelling. Regarding firms' potential market, the number of dwellings has a negative impact on quantity and the share of owner-occupiers seems to deter first adoptions. Everything else equal, they are both indicators of a larger market available for each firm, which could lower firms' need for differentiation. These coefficients are consistent with the positive impact of competition, measured by the number of firms in the same city. In other words, firms seem to suggest more state-of-the-art materials to their customers when they are located in more competitive environments. Finally, mean blue-collar wages were included to reflect local labor costs for contractors. As expected, higher labor costs are associated with a decrease in adoption, both inter and intra firm.

5.2 Extensions

Local word-of-mouth is not the only determinant behind the geographical aggregation of adopters. Local market characteristics also have a significant effect, meaning adoption is also driven by household demand. Hence inter-firm diffusion appears to be driven by those end-clients and not the spread of information among firms. Proximity to previous adopters does however have a positive effect on intra-firm diffusion. To further investigate the channel through which information may circulate between contractors, specification (1) in Table 3 displays results obtained with clustered standard errors at the store level. As most firms visit different stores during a given year, the "main" store was defined as the store where they spent the most. Only firms that had the same main store over the year were kept in the estimation sample. Estimation results

	(1)		(2)	
	Adoption	Quantity	Adoption	Quantity
Standard drywall (m^2)	0.000005	0.000005	0.000029***	0.000002
	(0.000004)	(0.000037)	(0.000006)	(0.000011)
Purchase frequency (%)	0.056447***	0.105551	0.042705***	0.059695***
	(0.005881)	(0.465064)	(0.002910)	(0.016344)
Normalized Herfindahl index	0.493849	0.380810	0.053295***	0.726059**
	(0.479148)	(1.523897)	(0.013772)	(0.305728)
Reference category: No employee				
1-2 workers	-0.037771	-0.157528	-0.000764	0.265791
	(0.098966)	(151.089223)	(0.097471)	(0.639725)
3-5 workers	0.013735	0.430212	0.064496	0.780108
	(0.101405)	(163.122395)	(0.104708)	(0.737823)
6-9 workers	0.011836	0.245311	0.092778	0.778786
	(0.122015)	(231.910637)	(0.111748)	(0.518880)
10-19 workers	-0.043138	0.646870	-0.027117	0.728883
	(0.134542)	(196.055039)	(0.115481)	(0.446421)
20-49 workers	-0.125543	2.530119	-0.019092	0.899149
	(0.174497)	(762.749853)	(0.135608)	(0.561291)
> 50 workers	-0.115002	1.478826	0.008052	1.018751
	(0.317179)	(1,026.611020)	(0.198886)	(0.662949)
Reference category: Interior finishing				
Real estate dev.	0.262044	-0.753077	0.295850	-0.527640
	(0.296578)	(154.217226)	(0.289388)	(0.412805)
Civil engineering	-0.016366	2.122693	-0.371106	1.241395
	(0.461526)	(363.892346)	(0.457120)	(0.977483)
Building construction	-0.020609	0.840401	-0.101529	0.654522*
	(0.111451)	(172.750115)	(0.090069)	(0.337827)
Demolition	-0.986077**	1.193233	-1.091584**	0.922918
	(0.448965)	(347.500805)	(0.452459)	(0.688000)
Elec., Plumbing, etc.	-0.341561***	1.048588	-0.379426***	0.654745
	(0.110958)	(256.698684)	(0.097851)	(0.528507)
Other specialized work	-0.265781***	0.732240	-0.221998***	0.186080
	(0.091580)	(101.170995)	(0.070027)	(0.269189)
Head office	-0.114028	-0.019871	-0.114950	-0.149365
	(0.089509)	(248.556976)	(0.089567)	(0.242698)
Experience	-0.002992	-0.027240	-0.002156	0.046896
	(0.003322)	(4.274294)	(0.002937)	(0.096005)
RGE	0.188472***	-0.297392	0.231110***	-0.215371
	(0.071502)	(2.186814)	(0.061253)	(0.338389)
Property prices	-0.000001**	0.000003	-0.000000	0.000001
	(0.000001)	(0.000061)	(0.000000)	(0.000001)
Competition	-0.000000	0.000608	-0.000008	0.001082**
	(0.000019)	(0.203373)	(0.000021)	(0.000545)
Sh. heat-sensitive (%)	-0.005562	0.022898	-0.002157	0.012474
	(0.005045)	(0.301820)	(0.004009)	(0.020321)
Dwellings	0.000002	-0.000073	0.000001	-0.000122**
	(0.000003)	(0.024331)	(0.000004)	(0.000050)
Sh. owners (%)	-0.007080	0.116116	-0.007002	0.082181
	(0.005646)	(6.081543)	(0.004310)	(0.058495)
Sh. houses (%)	0.009300***	-0.057067	0.008242***	-0.033394
	(0.003540)	(4.213211)	(0.002586)	(0.028714)
Med. disp. income	0.000017	-0.000292	0.000018	-0.000253
	(0.000015)	(0.006653)	(0.000011)	(0.000174)
Blue collar wages (€)	-0.112195*	-0.357388	-0.127457***	0.031679
	(0.057828)	(11.881018)	(0.046347)	(0.481141)
$\mathbb{1}_{>30m^2}$	1.980879***	3.426789	2.289837***	3.497761***
	(0.383200)	(4.771981)	(0.109988)	(0.237078)
γ_1	0.039153	0.354638	0.180704	0.390103*
	(0.051091)	(35.501012)	(0.450840)	(0.223201)
Standard drywall t-1			-0.000026***	-0.000008
			(0.000007)	(0.000009)
Habito t-1				-0.000232**
				(0.000104)
Observations	61,862	2,333	58,227	3,506
Groups	16,839	993	20,619	1,614
γ_2	1.7	1.1	0.1	1.3
Standard error	Main store cluster	Main store cluster	Robust	Robust

Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Extensions

on this sub-sample are consistent with those presented in Table 2 (2), except that γ_1 is non-significant, nor the normalized Herfindahl index. It supports the idea that contractors get information on products from their local store, either through exchanges with the staff or with other contractors.

The adoption index also becomes non-significant when introducing consumption lags in the regressors (Table 3, (2)). It is most probably due to the *de facto* exclusion of 2017 observations, which act as a baseline to estimate the effect of the adoption index. The coefficients associated with standard drywall purchase however remain consistent with previous results. The quantity of BA-13 drywall purchased in $t-1$ interestingly has a significantly negative effect on the probability of first adoption, while the quantity of Habito purchased in $t-1$ has a negative impact on the quantity of Habito purchased in t. It is consistent with the fact that a large share of first-adopters did not repeat their purchase. Building construction professionals are still more likely to buy larger quantities of Habito drywall, which can be linked to the scale of their activity and the fact that new buildings are much more strictly regulated than retrofits in France in terms of materials. It should also be noted that the impact of RGE on adoption is still significantly positive across all specifications, but it is non-significant on the quantity purchased.

6 Discussion and conclusion

This paper contributes to the literature on new technology diffusion by firms in several ways. There are very few papers exploiting trackable firm-level panel data, and none of them investigates the diffusion of an intermediate input. The econometric specification also allows for both spatial and time effects, which are usually studied separately. Estimation results show that (1) the characteristics of both the local market and the individual firm drive adoption, (2) only intra-firm diffusion is impacted by proximity to previous adopters, with information seemingly circulating through the stores visited and (3) store-level loyalty appears to be key determinant of the adoption process. These results also highlight the importance of accounting for intra-firm diffusion, as an increasing number of first adopters does imply that more households are getting the new drywall over time. The spatial clusterization of new adoptions appears to be due to local demand specificities as well as information circulating between firms. It hints at the fact that end-client demand contributes to the inter-firm diffusion locally.

As in all empirical applications, there are some limitations to this work. The dataset used is restricted to metropolitan France, which may be problematic in border areas. As France is part of the European market, companies are free to operate on both sides of the borders with neighboring countries. It means that that can not only interact with foreign companies that are not referenced in the SIRENE dataset, but they can also buy materials in other countries. It is mainly an issue regarding Southern borders, as prices are usually lower in Italy and Spain. More generally, the sales data does cover a wide range of companies, but it does not provide a complete picture of the French market. It is a common issue with scanner data, which is simultaneously very broad but still incomplete. Whether their clients are a representative subset of all French firms cannot be assessed, and there could be a selection bias. Finally, two issues are linked to the diffusion process more specifically. The data only covers the four years after the launch of the board, which is not a long period of time. Firms that chose to try it out are very early adopters, which typically have unobservable hidden characteristics. The results may also be specific to the Habito board and not to the construction sector, and it would be interesting to see how the diffusion processes of other innovations compare.

However limited, these results shine an interesting light on public policy issues. The French residential sector accounts for roughly 28% of final energy consumption (SDES 2020), making it a major environmental policy target. Facilitating the diffusion of green building materials among construction companies could be a way to achieve this goal, and it has not yet been directly addressed. The RGE label is the only energy-efficiency policy currently implemented that targets firms directly. It does favor new adoptions, but not the intensification of usage over time. As hiring a RGE contractor is a necessary requirement for households to access the main financial aid for energy retrofits, the positive impact of the label could solely indicate that reducing their financial burden allows them to ask for better products than the baseline. Its impact on intra-firm diffusion being zero or negative however indicates that this new technology was used for one-off projects, rather than a part of long-term strategies. Estimations results further suggest that material stores act as information hubs for contractors. In practice, they visit them several times a week, and it is a place to meet both other contractors and specialized vendors. A diffusion policy could thus rely on these local information hubs to spread knowledge about high-performance products. Finally, identifying which companies are more likely to offer state-of-the-art products to their clients and supporting their efforts could be effective, but not sufficient if end-consumers are left out of the equation. Household policies are currently limited to financial help for retrofits, and more focus could be put into providing them with information. Local policies could also be established to target areas where innovation uptake would be slow otherwise. It would be interesting to see if these results is specific to the Habito board, or if it holds up for other innovative products.

References

[1] Anna Alberini, Olha Khymych, and Milan Scasny. "Responsiveness to energy price changes when salience is high: Residential natural gas demand in Ukraine". In: *Energy Policy* 144 (2020), p. 111534.

[2] Jason Allen, C. Robert Clark, and Jean-François Houde. "Market structure and the diffusion of e-commerce: Evidence from the retail banking industry". In: *Bank of Canada Working Paper* (2009).

[3] Spyros Arvanitis and Marius Ley. "Factors determining the adoption of energy-saving technologies in Swiss firms: an analysis based on micro data". In: *Environmental and Resource Economics* 54.3 (2013), pp. 389–417.

[4] Thomas Astebro. "Sunk costs and the depth and probability of technology adoption". In: *The Journal of Industrial Economics* 52.3 (2004), pp. 381–399.

[5] Giuliana Battisti, Alessandra Canepa, and Paul Stoneman. "E-Business usage across and within firms in the UK: profitability, externalities and policy". In: *Research Policy* 38.1 (2009), pp. 133–143.

[6] Giuliana Battisti and Paul Stoneman. "Inter-and intra-firm effects in the diffusion of new process technology". In: *Research Policy* 32.9 (2003), pp. 1641–1655.

[7] Giuliana Battisti and Paul Stoneman. "The intra-firm diffusion of new process technologies". In: *International Journal of Industrial Organization* 23.1-2 (2005), pp. 1–22.

[8] Marie-Anne Belin and François Lefort. *Évaluation du dispositif "reconnu garant de l'environnement" (RGE)*. Conseil Général de l'Environnement et du Développement Durable, 2017.

[9] Andrea Bonaccorsi, Lucia Piscitello, and Cristina Rossi. “Explaining the territorial adoption of new technologies. A spatial econometric approach”. In: *Applied evolutionary economics and economic geography* 256 (2007).

[10] Timothy F. Bresnahan, Erik Brynjolfsson, and Lorin M. Hitt. “Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence”. In: *The quarterly journal of economics* 117.1 (2002), pp. 339–376.

[11] Anne Case. “Neighborhood influence and technological change”. In: *Regional science and urban economics* 22.3 (1992), pp. 491–508.

[12] Diego A. Comin, Mikhail Dmitriev, and Esteban Rossi-Hansberg. *The spatial diffusion of technology*. Tech. rep. National Bureau of Economic Research, 2012.

[13] John G. Cragg. “Some statistical models for limited dependent variables with application to the demand for durable goods”. In: *Econometrica: Journal of the Econometric Society* (1971), pp. 829–844.

[14] Stephen J. DeCanio and William E. Watkins. “Investment in energy efficiency: do the characteristics of firms matter?” In: *Review of economics and statistics* 80.1 (1998), pp. 95–107.

[15] Diansheng Dong, Chanjin Chung, and Harry M. Kaiser. “Modelling milk purchasing behaviour with a panel data double-hurdle model”. In: *Applied Economics* 36.8 (2004), pp. 769–779.

[16] Ping Du et al. “Barriers to the adoption of energy-saving technologies in the building sector: A survey study of Jing-jin-tang, China”. In: *Energy Policy* 75 (2014), pp. 206–216.

[17] Robin Dubin. “Estimating logit models with spatial dependence”. In: *New directions in spatial econometrics*. Springer, 1995, pp. 229–242.

[18] Timothy Dunne. “Plant age and technology use in US manufacturing industries”. In: *The RAND Journal of Economics* (1994), pp. 488–499.

[19] EIA. *Energy Outlook (2021)*. 2020.

[20] Eurostat. *Energy, transport and environment statistics — 2020 edition*. 2020.

[21] Danielle Galliano and Pascale Roux. “Organisational motives and spatial effects in Internet adoption and intensity of use: evidence from French industrial firms”. In: *The Annals of regional science* 42.2 (2008), pp. 425–448.

[22] Kenneth Gillingham, Richard G. Newell, and Karen Palmer. “Energy efficiency economics and policy”. In: *Annu. Rev. Resour. Econ.* 1.1 (2009), pp. 597–620.

[23] Ioannis Giotopoulos et al. “What drives ICT adoption by SMEs? Evidence from a large-scale survey in Greece”. In: *Journal of Business Research* 81 (2017), pp. 60–69.

[24] Jaime Gómez and Pilar Vargas. “Intangible resources and technology adoption in manufacturing firms”. In: *Research Policy* 41.9 (2012), pp. 1607–1619.

[25] William H Greene. “Accounting for excess zeros and sample selection in Poisson and negative binomial regression models”. In: (1994).

[26] Zvi Griliches. “Hybrid corn: An exploration in the economics of technological change”. In: *Econometrica, Journal of the Econometric Society* (1957), pp. 501–522.

[27] Heinz Hollenstein. “Determinants of the adoption of Information and Communication Technologies (ICT): An empirical analysis based on firm-level data for the Swiss business sector”. In: *Structural change and economic dynamics* 15.3 (2004), pp. 315–342.

[28] Bo E. Honoré and Ekaterini Kyriazidou. “Panel data discrete choice models with lagged dependent variables”. In: *Econometrica* 68.4 (2000), pp. 839–874.

[29] Pinar Karaca-Mandic, Robert J. Town, and Andrew Wilcock. “The effect of physician and hospital market structure on medical technology diffusion”. In: *Health services research* 52.2 (2017), pp. 579–598.

[30] Maryellen R. Kelley and Susan Helper. “Firm size and capabilities, regional agglomeration, and the adoption of new technology”. In: *Economics of Innovation and New technology* 8.1-2 (1999), pp. 79–103.

[31] Moon-Hyun Kim and Tae-Hyoung Tommy Gim. “Spatial Characteristics of the Diffusion of Residential Solar Photovoltaics in Urban Areas: A Case of Seoul, South Korea”. In: *International Journal of Environmental Research and Public Health* 18.2 (2021), p. 644.

[32] Doris Laepple et al. “Sustainable technology adoption: who and what matters in a farmer’s decision?” In: *European Review of Agricultural Economics* 44.5 (2017), pp. 810–835.

[33] Edwin Mansfield. “Intrafirm rates of diffusion of an innovation”. In: *The review of economics and statistics* (1963), pp. 348–359.

[34] Edwin Mansfield. *The economics of technological change*. 1968.

[35] Gilbert E. Metcalf and Kevin A. Hassett. “Measuring the energy savings from home improvement investments: evidence from monthly billing data”. In: *Review of economics and statistics* 81.3 (1999), pp. 516–528.

[36] Abolfazl Mohammadian, Murtaza Haider, and Pavlos S. Kanaroglou. “Homebuilders Choice Behaviour Analysis.” In: *Canadian Journal of Regional Science* 31.2 (2008).

[37] Craig Morton, Charlie Wilson, and Jillian Anable. “The diffusion of domestic energy efficiency policies: A spatial perspective”. In: *Energy Policy* 114 (2018), pp. 77–88.

[38] Dimitrios Pontikakis, Y. Lin, and Dilek Demirbas. “History matters in Greece: The adoption of Internet-enabled computers by small and medium sized enterprises”. In: *Information Economics and Policy* 18.3 (2006), pp. 332–358.

[39] RTE. *Bilan électrique 2019*. Tech. rep. RTE, 2019.

[40] Camilo Sarmiento and William W. Wilson. “Spatial modeling in technology adoption decisions: The case of shuttle train elevators”. In: *American Journal of Agricultural Economics* 87.4 (2005), pp. 1034–1045.

[41] SDES. *Chiffres clés de l’énergie. Edition 2020*. 2020.

[42] Paul Stoneman. “Intra-firm diffusion, Bayesian learning and profitability”. In: *The Economic Journal* 91.362 (1981), pp. 375–388.

[43] Paul Stoneman and Giuliana Battisti. “The diffusion of new technology”. In: *Handbook of the Economics of Innovation*. Vol. 2. Elsevier, 2010, pp. 733–760.

[44] Tobias Stucki and Martin Woerter. “Intra-firm diffusion of green energy technologies and the choice of policy instruments”. In: *Journal of Cleaner Production* 131 (2016), pp. 545–560.

[45] Patrick S. Ward and Valerien O. Pede. "Capturing social network effects in technology adoption: the spatial diffusion of hybrid rice in Bangladesh". In: *Australian Journal of Agricultural and Resource Economics* 59.2 (2015), pp. 225–241.

[46] Nikolas Zolas et al. *Advanced Technologies Adoption and Use by US Firms: Evidence from the Annual Business Survey*. Tech. rep. National Bureau of Economic Research, 2021.

N°2023 - 06 • APRIL 2023

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