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DIGITAL MICROBUSINESSES AND LOCAL ECONOMIC OUTCOMES IN THE UK

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EXECUTIVE SUMMARY

The microbusiness sector in the UK continues to play a pivotal role in driving both economic growth and employment. In 2023, there were 5.3 million microbusinesses (defined as businesses employing 0-9 people, excluding the employer), representing 95% of all businesses, 32% of total employment, and 21% of turnover (excluding the financial services sector)[1]. This represents an annual increase of 2% in the number of active microbusinesses in the UK compared to 2022.

Despite their significance, comprehensive data on microbusiness density remains limited. This is particularly true for digital microbusinesses, as there is no publicly available data source in the UK that classifies them as a distinct category. This data gap means digital microbusinesses are often underrepresented in policy discussions, with their contributions to the economy largely overlooked by researchers and policymakers.

This study builds on the findings from our 2023 report, *The Impact of Digital Microbusinesses on Local Economic Outcomes in the UK*, and uses newly available data to further address this knowledge gap. We utilise the most recent dataset on digital microbusiness density in the UK, provided by GoDaddy through its Venture Forward initiative.

This study builds on the previous report by incorporating more advanced modelling techniques. While linear regression was already employed in the earlier analysis, we have now introduced panel regression and random forest analysis. These new methods provide fresh insights into the relationships between digital microbusiness density and key local economic and labour market outcomes. Our findings reaffirm the strong association between digital microbusinesses and two critical indicators: (i) the number of jobs available per resident and (ii) annual pay for full-time workers.

It is important to note that the analysis does not establish any causal relationships.

[1] https://researchbriefings.files.parliament.uk/documents/SN06152/SN06152.pdf

Table 1 Summary of results

Economic outcome variable	2023 study - Headline findings	2024 study - Headline findings
Jobs density (baseline model)	■ We find that each additional microbusiness per resident in 2020 is associated with an average increase of approximately 7 jobs per resident in 2021 (1% level of significance)	■ The random forest analysis shows that microbusiness density improves the prediction of jobs density, confirming the strong statistical association.
Jobs density (model excluding the City of London and Westminster)	■ We find that each additional digital microbusiness per resident in 2020 is associated with an average increase of approximately 6 jobs per resident in 2021 (1% level of significance)	■ We find that each additional digital microbusiness per resident in 2021 is associated with an average increase of approximately 5 jobs per resident in 2022 (1% level of significance).
Median annual pay (full-time) (baseline model)	■ A 10% increase in the number of active digital microbusinesses between 2020 and 2021 is linked to an approximately £138 increase in median annual pay for full-time workers in 2021 (1% level of significance).	■ Using a panel regression model that controls for time-fixed effects, we find that a 10% year-on-year increase in microbusiness density leads to an annual £320 increase in median annual pay for full-time workers (1% level of significance). ■ The random forest analysis shows that microbusiness density improves the prediction of median annual pay for full-time workers, confirming the strong statistical association.
GDP (baseline model)	■ 10 additional digital microbusinesses per 1,000 residents in 2020 is associated with an approximate increase of	■ Despite not finding a clear link between digital microbusinesses and GDP through regression analysis, the random forest analysis shows that microbusiness density improves the prediction of GDP,

Economic outcome variable	2023 study - Headline findings	2024 study - Headline findings
	£37,000 in GDP for 2021 (1% significance).	showing that microbusiness density is statistically associated to higher GDP.
GDP (model excluding the City of London and Westminster)	■ 10 additional digital microbusinesses per 1,000 residents in 2020 is associated with an approximate increase of £18,000 in GDP for 2021 (1% significance).	-

Source: Frontier Economics analysis of GoDaddy proprietary dataset and UK public data (see Annex).

1 Introduction

The microbusiness sector in the UK remains a critical driver of economic growth and employment. In 2023, microbusinesses - defined as businesses employing 0-9 people, excluding the owner - accounted for 95% of all businesses in the UK. They contribute significantly to the economy, representing 32% of private sector employment and 21% of turnover (excluding the financial services sector)[2]. As such, microbusinesses play a pivotal role in supporting local economies, driving innovation, and fostering entrepreneurial activity. However, despite their contribution, these businesses often face challenges in gaining the visibility and support needed to maximise their impact on the broader economy.

One of the main barriers to understanding the full economic influence of microbusinesses, particularly digital microbusinesses, is the lack of comprehensive data. Microbusinesses are less likely to prioritise data collection and reporting due to limited resources, and exemptions from certain reporting requirements. This, combined with the lack of publicly available data in the UK categorising microbusinesses as "digital", makes it difficult to assess their contributions. As a result, digital microbusinesses are often overlooked in policy debates, and their role in driving economic growth and labour market performance is underappreciated.

GoDaddy, the world's largest platform for entrepreneurs, plays a key role in supporting microbusinesses worldwide. With over 20 million customers, including more than 60,000 in the UK, GoDaddy empowers microbusinesses by providing them with the tools they need to succeed online. We produced this research for GoDaddy as part of their Venture Forward initiative, which seeks to better understand the economic impact of digital microbusinesses by leveraging a unique dataset on digital microbusiness density across the UK.

Building on our 2023 report, *The Impact of Digital Microbusinesses on Local Economic Outcomes in the UK,* this study uses an updated and expanded version of the GoDaddy dataset. The analysis proceeds in three ways:

- It refreshes the previous linear regression analysis with more recent data to reaffirm the relationship between digital microbusiness density and local economic outcomes;
- It expands on the previous work by introducing panel data regression to account for changes over time; and
- It incorporates a random forest model, a machine learning algorithm, to explore the association between digital microbusinesses and local economic performance in a more flexible, non-linear context.

Through these methods, this study offers a more comprehensive understanding of the role digital microbusinesses play in supporting economic growth and labour market outcomes at the local level. It not only updates existing evidence but also provides new insights into the relationship between digital microbusiness density, job availability and wages.

[2] https://researchbriefings.files.parliament.uk/documents/SN06152/SN06152.pdf

2 Data

We built a panel dataset, including information on macroeconomic indicators, sociodemographic variables and digital microbusiness density. The dataset includes information from 2020 to 2023 for most of the variables included. Our proxy variable of digital microbusiness density is based on GoDaddy proprietary data and is calculated as the number of digital microbusinesses per resident in each geographic unit. The regression models use two different outcome variables (jobs density and median annual pay), as well as control variables, all of which were sourced from UK publicly available datasets:

- **Annual Population Survey (APS)** – A continuous household survey with approximately 320,000 respondents across the UK. The APS covers a range of topics including employment, unemployment, housing, ethnicity, religion, health, and education. The latest available data extends until 2023.
- **Annual Survey of Hours and Earnings (ASHE)** – Conducted annually in April, ASHE is based on a sample of employee jobs drawn from HM Revenue and Customs' PAYE records. It provides detailed information on earnings, hours worked, and employee characteristics such as age, sex, occupation, and industry. ASHE remains the most comprehensive source on the structure and distribution of earnings in the UK, with data available up to 2023.
- **Census** – Conducted every 10 years, the Census provides a comprehensive overview of all individuals and households in England and Wales. The latest Census data is available from 2021.
- **Jobs density data** - Published by the Office for National Statistics, this data is available through 2022.
- **Regional Gross Domestic Product (GDP)** - Also published by the Office for National Statistics, regional GDP and Gross Value Added (GVA) data are available up to 2022.
- **Ofcom data** – This includes broadband coverage information underpinning the Connected Nations report, with data available through 2023.

Due to data limitations, the analysis was conducted at the local authority level, even though some data is also available at the parliamentary constituency level.[3]

[3] There are 317 local authorities and 650 parliamentary constituencies in the UK.

3 Results

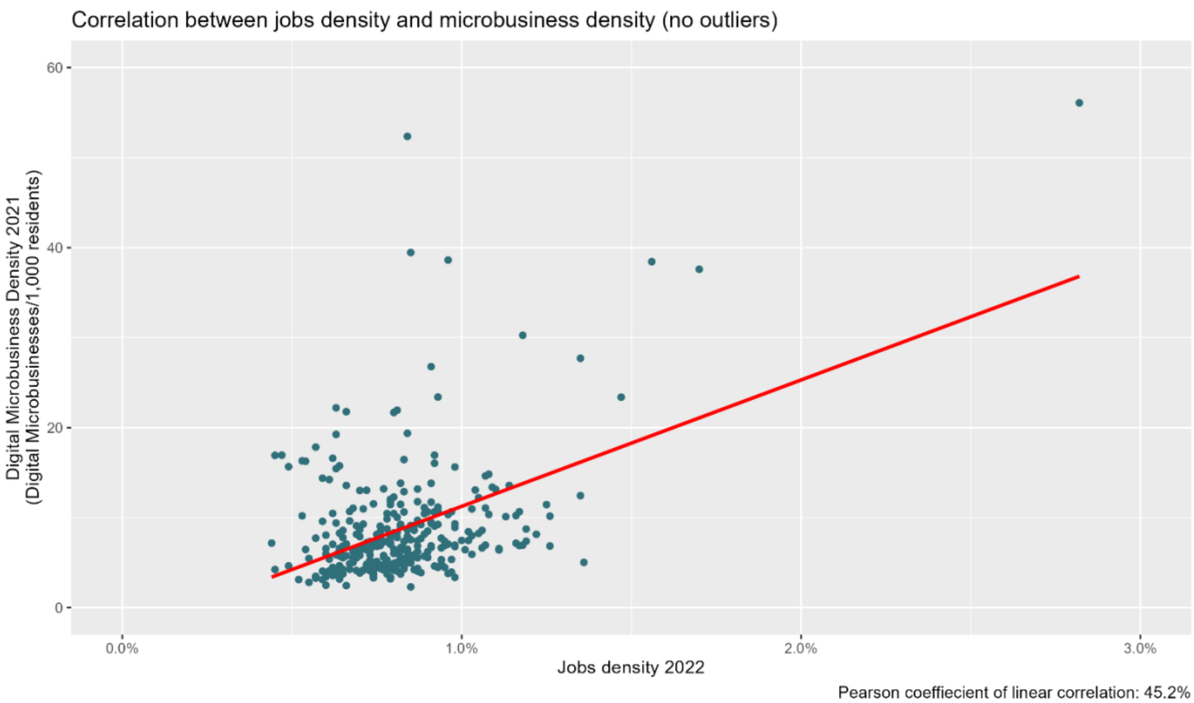
3.1 Descriptive statistics

The data reveals a positive, unconditional correlation between digital microbusiness density and key economic performance metrics, specifically jobs density and median annual pay for full-time workers. However, as illustrated in the following figures, the correlation between digital microbusiness density and jobs density is notably influenced by outliers, such as the City of London and Westminster. These areas exhibit exceptionally high jobs density but have relatively small resident populations, which skews the overall relationship.

Figure 1 Correlation between jobs density in 2022 and digital microbusiness density in 2021 across local authorities including outliers

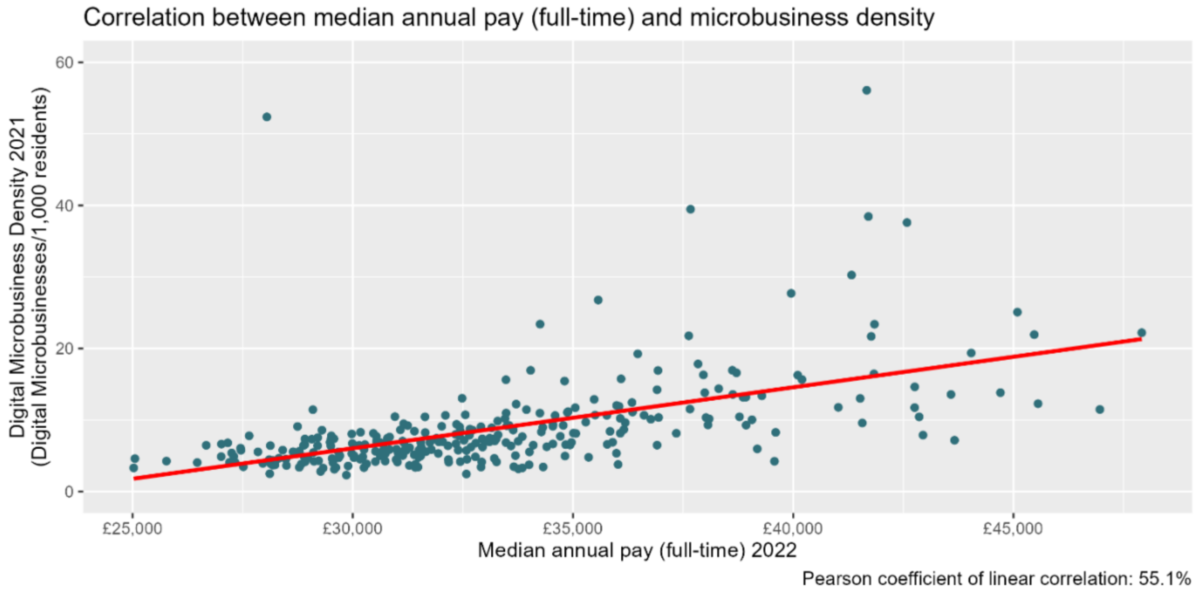
Source: *Frontier Economics analysis of GoDaddy proprietary data and UK public datasets (see Annex)*
Note: *Includes all local authorities in the sample*

Figure 2 Correlation between jobs density in 2022 and digital microbusiness density in 2021 across local authorities excluding outliers



Source: Frontier Economics analysis of GoDaddy proprietary data and UK public datasets (see Annex)
Note: Excludes the City of London and Westminster

Figure 3 Correlation between median annual pay of full-time workers in 2022 and digital microbusiness density in 2021 across local authorities



Source: Frontier Economics analysis of GoDaddy proprietary data and UK public datasets (see Annex)
Note: Includes all local authorities in the sample

3.2 Results of econometric analysis

3.2.1 Jobs density

We performed a linear regression analysis to examine the relationship between jobs density in 2022 and digital microbusiness density in 2021 at the local authority level. The results indicate that, on average, each additional digital microbusiness per resident in 2021 is associated with an increase of approximately 4.7 jobs per resident in 2022, controlling for other factors and excluding the City of London and Westminster from the analysis. In practical terms, this means that each additional digital microbusiness corresponds to approximately 5 new jobs.

This result suggests that the creation of a new microbusiness may generate employment beyond its own workforce, as 79% of microbusinesses have between 0 and 4 employees[4], and the analysis captures the impact within the first year of the business's creation. One possible explanation is that employees newly hired by microbusinesses increase demand for goods and services from local suppliers, prompting these suppliers to hire additional staff. It

4 How well do you know your microbusinesses? A report for the LGA from Shared Intelligence (2021). Available at: [How well do you know your microbusinesses? | Local Government Association]

is also important to note that the model is able to explain close to 70% of the fluctuations in jobs density [5].

See Figure 4 in Annex for more detail.

3.2.2 Median annual pay

Panel data regression analysis shows that a higher microbusiness density is associated with a higher median annual pay. In particular, a 10% increase in microbusiness density leads to £320 increase in median annual pay for full-time workers, everything else being equal. This represents 20% of the average increase in median annual pay for full time workers across local authorities registered between 2020 and 2022[6].

These results are robust to the inclusion of time fixed effects. All panel regressions used are fixed-effects models, which control for changes over time that are common to all local authorities in the UK and that could influence median annual pay, such as national economic trends or policy changes. By accounting for time fixed effects, we ensure that the estimated impact of microbusiness density on pay is not influenced by broader trends or events occurring during the study period, such as COVID-19 pandemic, inflation or shifts in labour market conditions between 2020 and 2022.

The results also indicate that the availability of Super-Fast Broadband plays a role in supporting income, as a one-percentage-point increase in broadband availability is associated with an increment of about £90 in median annual pay.

See Figure 5 in Annex for more detail.

3.3 Results of random forest analysis

We have also used a random forest—a machine learning model used for prediction—to evaluate the relative importance of each predictive variable on the economic outcome of interest. This has been done to assess microbusiness density's relative importance compared to other determinants of economic outcomes.

To achieve this, the model splits the dataset into two subsets: a training subset and a test subset. Typically, about 70-80% of the data is used for training, and the remaining 20-30% is reserved for testing. This separation allows the model to be trained on part of the data and tested on another part, which was not seen during training, to ensure that the model performs well on data that was not used to train the model.

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5 As indicated by the model's R-squared value (68%), which is a measure of its goodness of fit.

6 The average increase in median annual pay for full time workers across local authorities was £1,574, according to the data employed in this study. Moreover, the average median annual pay per full time worker was £33,246 in 2022.

In addition to making predictions, a random forest model helps us understand how important each variable is in influencing the outcome. To do this, the model looks at how much each variable improves the accuracy of the predictions when it is used to divide the data into groups. The model splits the data into smaller groups (the "trees" of the random forest, also referred to as "nodes") based on one variable. If this split results in more similar or "pure" nodes — where the outcomes are more alike—then that variable is considered important. In simpler terms, the model checks if using a certain variable helps make better predictions by creating more accurate groupings, or "increasing the purity of the nodes".

In the end, the relative importance of a variable is measured through a score called "incremental node purity", a proxy of how much the variable improves the model's accuracy across all the decision trees in the forest. The higher this value, the more significant that variable is in helping the model make better predictions.

Random forest models offer two main advantages: they excel in handling datasets with complex, non-linear relationships between variables, and they are highly resistant to overfitting.[7] However, these models are often considered "black boxes", meaning that interpreting the individual contributions of explanatory variables can be challenging. Additionally, because they exclusively rely on identifying correlations, random forest models cannot be used to establish causal relationships between variables.

In our analysis, the random forest reveals that even after accounting for the effect of other determinants of economic outcomes, microbusiness density provides additional information and improves the prediction of the outcome variable – the "incremental node purity" of microbusiness density is always significantly different from zero. The random forest employed finds that out of the 59 variables tested, microbusiness density is ranked 6th in predicting the median annual pay, 16th in predicting the unemployment rate, 32nd in predicting the GDP and 37th in predicting the jobs density.

These results strengthen our confidence on the existence of a strong association between microbusiness density and economic outcomes, underlying the relevance and value of microbusinesses for economic analysis and reinforcing the need to consider them alongside other commonly analysed determinants.

3.4 Limitations of the analysis

We identify three main limitations from the analysis:

- Causality: the regression and random forest results do not necessarily imply a causal relationship, but provide information on how the variables are associated.

[7] Overfitting occurs when a model fits too closely to the training data, capturing noise and random fluctuations instead of general trends, resulting in poor performance on new data.

- Direction of relationship: The random forest analysis indicates the strength of the correlation between variables but not the direction (positive or negative) of this association.

- Proxy on digital microbusinesses: the analysis uses the number of GoDaddy customers as a proxy of digital microbusiness density, however, it may not truly resemble actual digital microbusiness density. An increase in the number of GoDaddy customers can occur due to a rise in the number of digital microbusiness within a geographical area or due to the acquisition of a client who switch to GoDaddy from another competitor.

4 Conclusion

Using new data and a broader set of methodologies, this refreshed study strengthens the evidence base showing a strong positive association between digital microbusiness density and local economic performance. Our findings reaffirm that digital microbusinesses play a significant role in fostering economic growth at the local level. The regression analyses indicate that regions with a higher density of digital microbusinesses tend to have more jobs available per resident and higher annual pay for residents. Additionally, the random forest models suggest that digital microbusiness density is strongly associated with other key measures of economic activity, such as GDP and unemployment.

While this study provides valuable insights into the correlations and relationships between digital microbusinesses and economic outcomes, it is important to note that no causal relationships have been established.

In light of these findings, future research efforts should focus on expanding the range of data sources available, deepening the time frame perspective to explore the consistency of the identified effects and exploring additional dimensions of digital microbusiness activity. This will provide a deeper understanding of their role in shaping regional and local economies.

Annex A - Annex

Figure 4 Regression of jobs density in 2022 on the microbusiness density in 2021, local authority level

	Dependent variable:
	jobsdensity_2022
md_abs_2021	4.728***
	(1.759)
I(gdp_current_market_prices_m * 1e+06)	0.000***
	(0.000)
sfbb_availability_percent_premises	-0.002
	(0.003)
level_3_qualifications	0.012***
	(0.005)
level_4_qualifications_and_above	0.002*
	(0.001)
population_nomis	-0.00000***
	(0.00000)
regionLondon	-0.125***
	(0.036)
Constant	0.725**
	(0.297)
Observations	268
R2	0.688
Adjusted R2	0.680
Residual Std. Error	0.125 (df = 260)
F Statistic	82.003*** (df = 7; 260)
Note:	*p<0.1; **p<0.05; ***p<0.01

Source: Frontier Economics analysis of GoDaddy proprietary dataset and UK public data (see Annex)

Note: The model excludes outliers (The City of London and Westminster).

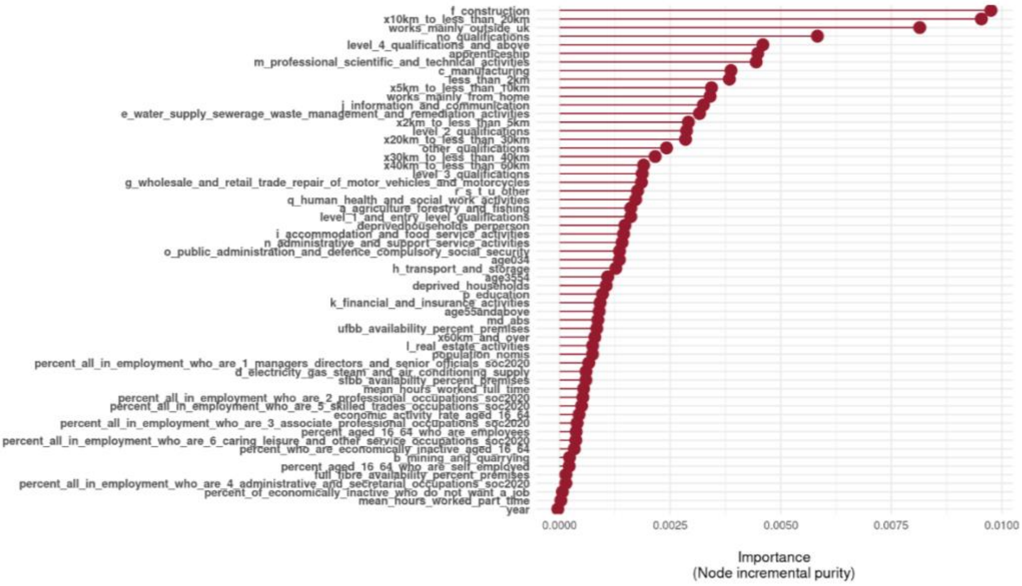
Figure 5 Panel regression of median annual pay of full-time workers on the log of the level of digital microbusiness density, local authority level, 2020-2022

	Dependent variable: median_annual_pay_full_time (1)	(2)
log(md_abs)	3,187.579***	3,154.377***
	(301.792)	(288.535)
sfbb_availability_percent_premises	87.051**	47.545
	(41.769)	(40.328)
age034	-0.039***	-0.040***
	(0.009)	(0.009)
age3554	0.063***	0.066***
	(0.017)	(0.016)
h_transport_and_storage	122.668	148.887*
	(80.399)	(76.948)
percent_all_in_employment_who_are_1_managers_directors_and_senior_officials_soc2020	288.291***	298.139***
	(36.380)	(34.806)
percent_all_in_employment_who_are_2_professional_occupations_soc2020	226.518***	222.421***
	(22.075)	(21.111)
factor(year)2022		1,593.786***
		(228.344)
Constant	29,990.240***	32,669.500***
	(4,308.105)	(4,136.148)
Observations	514	514
R2	0.655	0.685
Adjusted R2	0.650	0.680
Residual Std. Error	2,670.272 (df = 506)	2,552.624 (df = 505)
F Statistic	136.998*** (df = 7; 506)	137.267*** (df = 8; 505)
Note:		*p<0.1; **p<0.05; ***p<0.01

Source: Frontier Economics analysis of GoDaddy proprietary data and UK public datasets (see Annex)

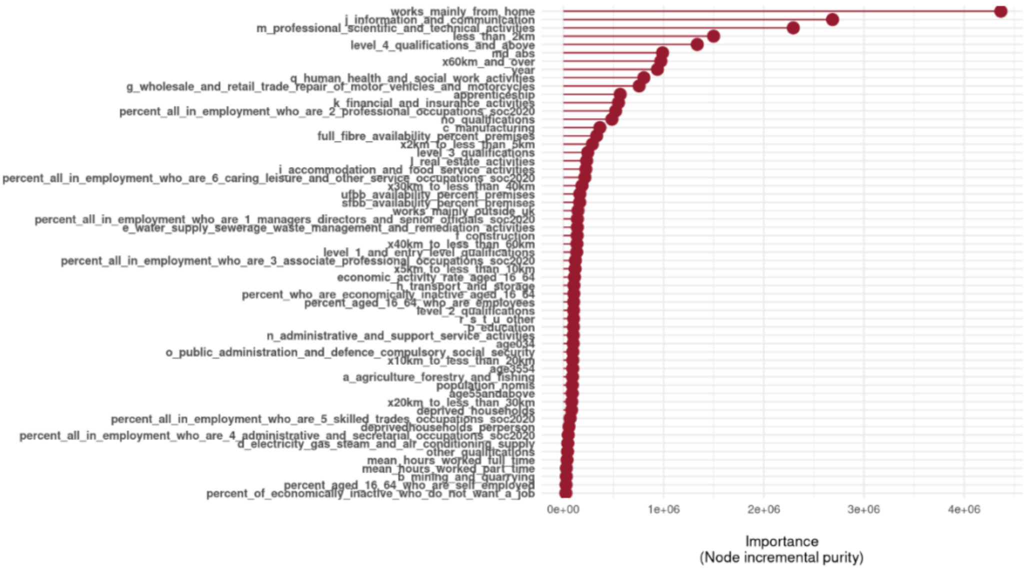
Note: Model 2 includes time fixed effects. As seen in Figure 3, the variable median annual pay has minor, if any, outliers. For that reason, these regressions were conducted in the entire sample, though results are robust to the exclusion of outliers.

Figure 6 Microbusiness density is ranked 37th for predicting jobs density in the random forest model



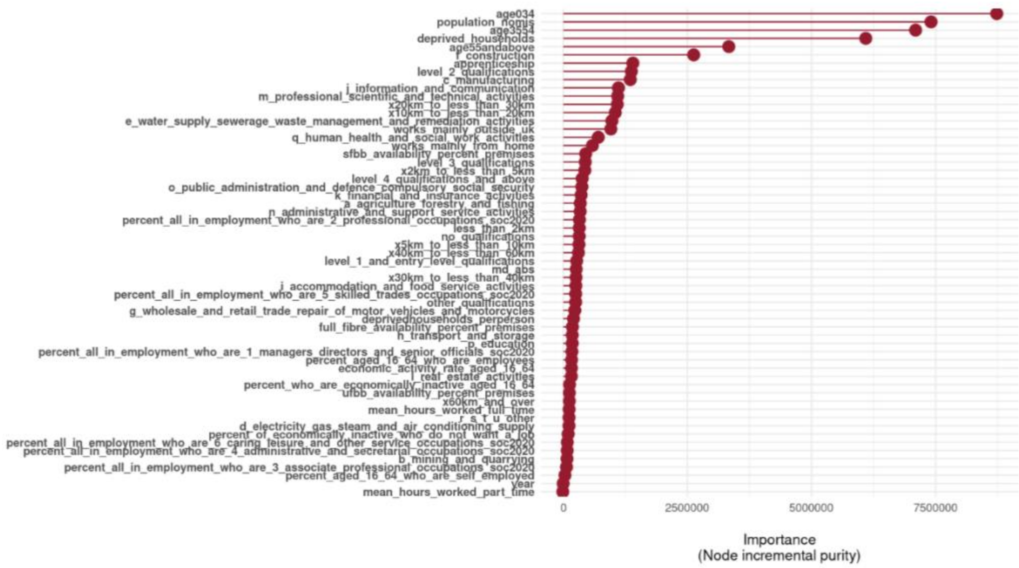
Source: Frontier Economics analysis of GoDaddy proprietary data and UK public datasets (see Annex)

Figure 7 Microbusiness density is ranked 6th for predicting median annual pay in the random forest model



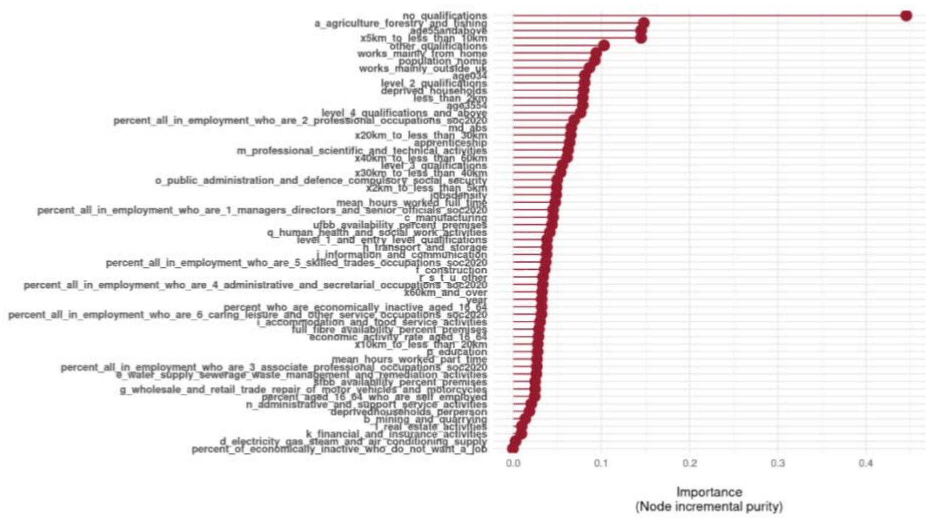
Source: Frontier Economics analysis of GoDaddy proprietary data and UK public datasets (see Annex)

Figure 8 Microbusiness density is ranked 32nd for predicting GDP in the random forest model



Source: Frontier Economics analysis of GoDaddy proprietary data and UK public datasets (see Annex)

Figure 9 Microbusiness density is ranked 16th for predicting unemployment rate in the random forest model



Source: Frontier Economics analysis of GoDaddy proprietary data and UK public datasets (see Annex)

Table 2 Breakdown of the variables contained in the final dataset

Variable	Source	Description
count	GoDaddy proprietary data	Number of GoDaddy's customers in a given parliamentary constituency
md	GoDaddy proprietary data	Number of GoDaddy's customers per 100 people in a given parliamentary constituency
medianannualpayFT	Annual Survey of Hours and Earnings	Median annual pay for full-time workers
medhrlypayFT	Annual Survey of Hours and Earnings	Median hourly pay for full-time workers
medhoursworkedFT	Annual Survey of Hours and Earnings	Median hours pay for full-time workers
MeanannualpayFullTime	Annual Survey of Hours and Earnings	Mean annual pay for full-time workers
MeanhourlypayFullTime	Annual Survey of Hours and Earnings	Mean hourly pay for full-time workers
MeanhoursworkedFullTime	Annual Survey of Hours and Earnings	Mean hours pay for full-time workers
GVAcurrentbasicpricesM	Office for National Statistics	Nominal GVA (£ millions)
GDPcurrentmarketpricesM	Office for National Statistics	Nominal GDP (£ millions)
jobsdensity	Job density	Number of jobs per resident aged 16-64
totaljobs	Job density	Total number of jobs
emplrate	Annual Population Survey	Employment rate for those aged 16-64
unemplrate	Annual Population Survey	Unemployment rate for those aged 16-64
Employees1664	Annual Population Survey	Share of those aged 16-64 who are employees
Selfemployed1664	Annual Population Survey	Share of those aged 16-64 who are self-employed

Variable	Source	Description
Economicactivityrate1664	Annual Population Survey	Economic activity rate for those aged 16-64
Economicallyinactive1664	Annual Population Survey	Share of those aged 16-64 who are economically inactive
Economicallyinactivewantinga	Annual Population Survey	Share of the economically inactive who want a job
Economicallyinactivenotwantin	Annual Population Survey	Share of the economically inactive who do not want a job
Ethnicminorityemploymentrate	Annual Population Survey	Employment rate for those aged 16-64 who are from an ethnic minority
Ethnicminorityunemploymentrat	Annual Population Survey	Unemployment rate for those aged 16-64 who are from an ethnic minority
Economicallyinactiveethnicmin	Annual Population Survey	Share of ethnic minority aged 16-64 who are economically inactive
share_of_managers	Annual Population Survey	Share of those in employment who are managers and senior officials
share_in_professional_occup	Annual Population Survey	Share of those in employment who work in professional occupations
share_in_associate_profess_occup	Annual Population Survey	Share of those in employment who work in associate professions and tech occupations
share_in_admin_secretarial_occup	Annual Population Survey	Share of those in employment who work in administrative and secretarial occupations
share_in_skilled_trade_occup	Annual Population Survey	Share of those in employment who work in skilled trade occupations
share_in_personal_service_occup	Annual Population Survey	Share of those in employment who work in personal service occupations
share_in_sales_customserv_occup	Annual Population Survey	Share of those in employment who work in sales and customer service occupations
share_in_process_plant_machine	Annual Population Survey	Share of those in employment who work in process, plant and machine operatives
share_in_elementary_occup	Annual Population Survey	Share of those in employment who work in elementary occupations

Variable	Source	Description
share_in_agriculture	Census	Share of workers in the agriculture, forestry and fishing industry
share_in_mining	Census	Share of workers in the mining and quarrying industry
share_of_manufacturing	Census	Share of workers in the manufacturing industry
share_in_water_supply_sewerage	Census	Share of workers in the water supply, sewerage, waste management and remediation activities industry
share_in_construction	Census	Share of workers in the construction industry
share_in_trade_repair_motor_vehi	Census	Share of workers in the wholesale and retail trade and repair of motor vehicles and motorcycles industry
share_in_transport_storage	Census	Share of workers in the transport and storage industry
share_in_accommodation_food	Census	Share of workers in the accommodation and food service activities industry
share_in_information_communica	Census	Share of workers in the information and communication industry
share_in_finance_insurance	Census	Share of workers in the financial and insurance activities industry
share_in_real_estate	Census	Share of workers in the real estate activities industry
share_in_science_technical_indu	Census	Share of workers in the professional, scientific and technical activities industry
share_in_admin_support	Census	Share of workers in the administrative and support service activities industry
share_in_public_admin	Census	Share of workers in the public administration
share_in_education	Census	Share of workers in the education industry
share_in_health_social_work	Census	Share of workers in the human health and social work activities industry
share_in_other_industries	Census	Share of workers in other industries

Variable	Source	Description
withNVQ1aged1664	Annual Population Survey	Share of those aged 16-64 with NVQ1 qualifications
withNVQ2aged1664	Annual Population Survey	Share of those aged 16-64 with NVQ2 qualifications
withNVQ3aged1664	Annual Population Survey	Share of those aged 16-64 with NVQ3 qualifications
withNVQ4aged1664	Annual Population Survey	Share of those aged 16-64 with NVQ4 qualifications
withotherqualificationsNVQ	Annual Population Survey	Share of those aged 16-64 with other NVQ qualifications
Noqualifications	Census	The share of residents with no qualifications
Level2qualifications	Census	The share of residents whose highest qualification is an intermediate diploma
Apprenticeship	Census	The share of residents whose highest qualification is an apprenticeship qualification
Level3qualifications	Census	The share of residents whose highest qualification is a high school diploma
Level4qualificationsorabove	Census	The share of residents whose highest qualification is a bachelor degree or higher
Otherqualifications	Census	The share of residents with vocational, work-related or other qualifications
distance_to_work_upto2km	Census	The share of workers for whom the distance to the workplace is less than 2km
distance_to_work_upto5km	Census	The share of workers for whom the distance to the workplace is less than 5km
distance_to_work_upto10km	Census	The share of workers for whom the distance to the workplace is less than 10km
distance_to_work_upto20km	Census	The share of workers for whom the distance to the workplace is less than 20km

Variable	Source	Description
distance_to_work_upto30km	Census	The share of workers for whom the distance to the workplace is less than 30km
distance_to_work_upto40km	Census	The share of workers for whom the distance to the workplace is less than 40km
distance_to_work_upto60km	Census	The share of workers for whom the distance to the workplace is less than 60km
distance_to_work_beyond60km	Census	The share of workers for whom the distance to the workplace is greater than 60km
Worksmainlyfromhome	Census	The share of workers who mainly work from home
Worksmainlyatanoffshoreinst	Census	The share of workers who mainly work at an offshore premise
Age034	Population Estimates/Projections	The share of population aged 0 to 34
Age3554	Population Estimates/Projections	The share of population aged 35 to 54
Age55andabove	Population Estimates/Projections	The share of population aged 55 and above
SFBBavailabilitypremises	Ofcom	Share of premises with Super-Fast broadband
UFBB100Mbitsavailability	Ofcom	Share of premises with Ultra-Fast broadband
FullFibreavailabilitypremi	Ofcom	Share of premise with Full Fibre availability
Gigabitavailabilitypremises	Ofcom	Share of premises with Gigabit availability
unabletoreceive2Mbits	Ofcom	Share of premise unable to receive 2Mbit/s
unabletoreceive5Mbits	Ofcom	Share of premise unable to receive 5Mbit/s
unabletoreceive10Mbits	Ofcom	Share of premise unable to receive 10Mbit/s

Variable	Source	Description
unabletoreceive30Mbits	Ofcom	Share of premise unable to receive 30Mbit/s
belowtheUSO	Ofcom	Share of premises below the Universal Service Obligation
withNGA	Ofcom	Share of premises with Next Generation Access
abletoreceiveBBfromFWA	Ofcom	Share of premises able to receive broadband from Fixed Wireless Access
with2Mbitsspeed	Ofcom	Share of premises with < 2Mbit/s speed
with25Mbitsspeed	Ofcom	Share of premises with > 2 and < 5Mbit/s speed
with510Mbitsspeed	Ofcom	Share of premises with > 5 and < 10 Mbit/s speed
with1030Mbitsspeed	Ofcom	Share of premises with > 10 and < 30 Mbit/s speed
with30300Mbitsspeed	Ofcom	Share of premises with > 30 and < 300 Mbit/s speed
with300Mbitsspeed	Ofcom	Share of premises with > 300 Mbit/s speed

Source: Frontier Economics based on GoDaddy proprietary data and UK public datasets.
Note: [Insert Notes]