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Intuit QuickBooks Small Business Index: A New Employment Series for the US, Canada, and the UK

Ufuk Akcigit, Raman Singh Chhina, Seyit M. Cilasun, Javier Miranda, Eren Ocakverdi, and Nicolas Serrano-Velarde

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Becker Friedman Institute
FOR ECONOMICS AT UCHICAGO

5757 S. University Ave.
Chicago, IL 60637
Main: 773.702.5599
bfi.uchicago.edu

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The primary purpose of this paper is to provide information on the methodology used to create the Intuit QuickBooks Small Business Index. Ufuk Akcigit is a paid independent contractor for Intuit Inc. The authors retained complete control over the content of this paper. Intuit reviewed the data product and endorsed measures to protect against unauthorized disclosure of confidential information and business-sensitive data. Statistical complications provided are anonymous and do not disclose information on individual QuickBooks subscribers or their employees. All information shared follows Intuit's Data Stewardship Principles and is in accordance with Intuit's Global Privacy Statement.

At least one co-author has disclosed additional relationships of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w31350

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ABSTRACT

Small and young businesses are essential for job creation, innovation, and economic growth. Even most of the superstar firms start their business life small and then grow over time. Small firms have less internal resources, which makes them more fragile and sensitive to macroeconomic conditions. This suggests the need for frequent and real-time monitoring of the small business sector's health. Previously this was difficult due to a lack of appropriate data. This paper fills this important gap by developing a new Intuit QuickBooks Small Business Index that focuses on the smallest of small businesses with at most 9 workers in the US and the UK and at most 19 workers in Canada. The Index aggregates a sample of anonymous QuickBooks Online Payroll subscriber data (QBO Payroll sample) from 333,000 businesses in the US, 66,000 in Canada, and 25,000 in the UK. After comparing the QBO Payroll sample data to the official statistics, we remove the seasonal components and use a Flexible Least Squares method to calibrate the QBO Payroll sample data against official statistics. Finally, we use the estimated model and the QBO Payroll sample data to generate a near real-time index of economic activity. We show that the estimated model performs well both in-sample and out-of-sample. Additionally, we use this analysis for different regions and industries.

Ufuk Akcigit Department
of Economics University
of Chicago 1126 East 59th
Street Saieh Hall, Office
403 Chicago, IL 60637
and NBER
uakcigit@uchicago.edu

Raman Singh Chhina
University of Chicago
Department of Economics
1126 E. 59th Street
Chicago, IL 60637
rschhina@uchicago.edu

Seyit M. Cilasun
Department of Economics
TED University
Ziya Gokalp Cad., No.48
06420 Kolej
Ankara
Turkey
seyit.cilasun@tedu.edu.tr

Javier Miranda
Friedrich-Schiller University
Kleine Märkerstraße 806108
Halle (Saale), Saxo D-06108
Germany
and Halle Institute for Economic Research
Javier.Miranda@iwh-halle.de

Eren Ocakverdi
Independent Researcher
erenocak@gmail.com

Nicolas Serrano-Velarde
Bocconi University
Via Roentgen 1
20135 Milan
Italy
nicolas.serranovelarde@unibocconi.it

1 Introduction

Small and young businesses are essential for job creation, innovation, and economic growth (Birch, 1987; Neumark, Wall, and Zhang, 2011; Haltiwanger, Jarmin, and Miranda, 2013; Akcigit and Kerr, 2018).[1] According to the most recent US Bureau of Labor Statistics and US Census Bureau numbers, businesses with less than 10 workers account for about 80% of all employers in the US and employ more than 13 million workers (Figure 1). Moreover, 93% of businesses start their lives very small (<10 employees) and grow over time (Figure 2). These businesses are particularly sensitive to business cycles, and are early indicators of economic activity (Fort et al., 2013; Asturias et al., 2021). Despite the major role small businesses play, real-time data about their performance are hard to produce due to various data limitations. The coverage of small businesses is either very poor in small-scale surveys, or their statistics are revealed with a lag of months if not years.[2] These limitations make it hard to monitor the overall performance of small businesses in real-time and design timely policies. Our project is an attempt to fill this gap by providing a new and unique index on the smallest of small businesses in the US, Canada, and the UK. A timely series of small business activity might be particularly useful for policy makers, researchers, and industry alike.

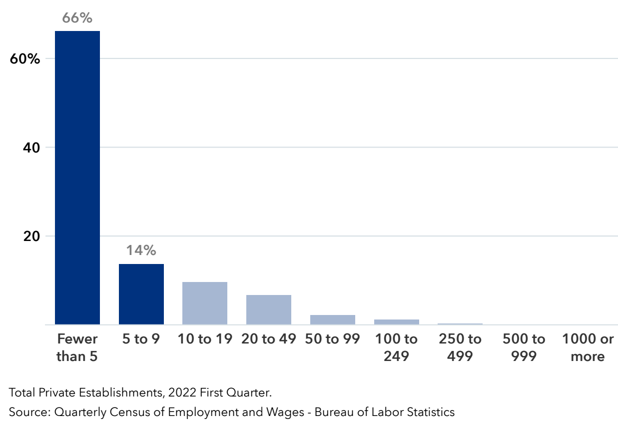


Figure 1: Firm Size Distribution

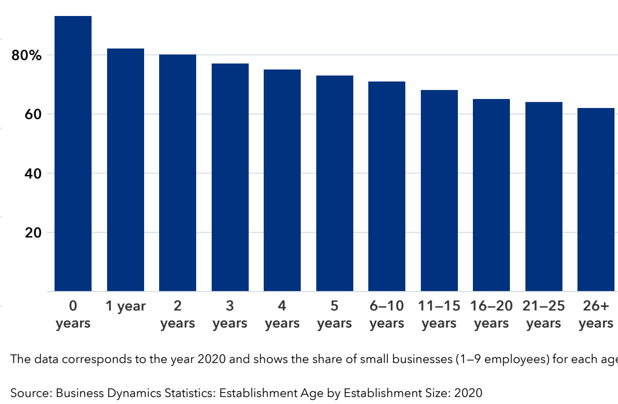


Figure 2: Share of small firms (1–9 employees) by age

To develop a timely indicator of small business activity we collaborate with Intuit — a global financial technology platform with a large presence in small business accounting.[3] Through this collaboration, following Intuit's Data Stewardship Principles, and in accordance with Intuit's Global Privacy Statement, we work alongside Intuit's data analytics team to build the Intuit

[1]Despite this fact, Akcigit and Ates (2022) and Akcigit and Goldschlag (2023) have shown that innovation and inventors have been shifting more and more toward large incumbents in recent decades.

[2]The more timely indicators include the Job Openings and Labor Turnover Series (JOLTS) from the Bureau of Labor Statistics, and the Business Trends and Outlook Survey (BTOS) from the Bureau of the Census for the US. These are survey-based. JOLTS produces a quantitative jobs creation series, whereas BTOS produces a broad series of business sentiment indexes. The UK produced measures of job flows for small businesses from the Interdepartmental Business Register, but production of these data was discontinued as of the last quarter of 2019. Canada produces an employment series for small businesses from labor force surveys that is extremely timely.

[3]As of July 2022, Intuit served 7.1 million online paying small business customers and 17.6 million paid workers on its platform.

QuickBooks Small Business Index (referred to as the QuickBooks Index) following the processes outlined in this paper. As researchers we never see customer desegregated data. Intuit aggregates and anonymizes customer data from a sample of QuickBooks Online Payroll subscribers (referred to as QBO Payroll sample) according to our specifications.[4]

Our business indicator is similar in spirit to the Bureau of Labor Statistics (BLS), Business Employment Dynamics (BED), which we use to calibrate our data for the US. We focus on the small businesses segment of the BED, and seek to create a timely monthly series to be released at the beginning of the month to capture the previous month's activity. We develop our methodology on the US data and extend it to create similar series also for the UK and Canada. For the UK and Canada we use timely survey data to calibrate our index since time series from the full administrative data are currently not available. Survey data are necessarily more noisy and subject to sampling and non-sampling errors. We hope to be able to partner with the ONS and Stats Canada to create a series targeting official benchmark data like we do for the US. In all cases, we use official products from national statistical offices to calibrate our series.

Our effort is not unique. Indicators produced with private industry data have a long history of use and continue to be refined (Cajner et al., 2018, 2022). For example, ADP's payroll data are used to construct an index of labor market conditions that is able to provide information about employment in the economy in near real time.[5] Our series differs in that we target specifically the smallest of small businesses, a business segment Intuit covers particularly well. Other small business indices include the US Chamber of Commerce Quarterly Small Business Index based on a convenience sample survey, and the Monthly Small Business Jobs Index from Paychex-IHS Markit using payroll data from approximately 350,000 small business Paychex clients. We differ from these efforts in that we aim to be representative of small business activity by using the QuickBooks Payroll data to target the BLS Business Employment Dynamics official net job creation series. For Canada, we use Labor Force Survey (LFS) data to calibrate our series. For the UK we use job vacancy data as our target series since this is the only data currently produced on business dynamics for small businesses.[6]

In this paper, we compare the QuickBooks Index for the US against high quality government statistics — the BLS's quarterly BED, and monthly Job Openings and Labor Turnover Series (JOLTS). Our indicator performs well and is able to capture the start of the COVID-19 shock as well as the quick recovery. We target the BED because its growth measures are derived from

[4]The sample is composed of a subset of the Intuit QuickBooks Online Payroll subscribers and does not include QuickBooks Desktop users.

[5]This index uses the BLS Quarterly Census of Employment and Wages (QCEW) as its benchmark. The BED is the private sector subset of the QCEW and includes measures of business dynamism which we are interested in.

[6]Employment data from Statistics Canada's LFS and vacancy data from the UK's Office of National Statistics are released 10 days after the end of the reference month. That is only about 10 days after the projected release of the Intuit indicator. These surveys are subject to sampling and non-sampling errors in ways that we do not fully understand given limited official releases from administrative records. Our preference would be to use administrative data instead. We are currently exploring the feasibility of doing this.

comprehensive administrative data and are not subject to sampling error. We blend the BED with JOLTS data to create a higher frequency series. The procedure is such that quarterly changes are governed by the BED, while higher frequency monthly changes are derived from the JOLTS data. We show that our aggregated near real time monthly estimates help forecast future values of the quarterly BED. We see the estimates generated from QBO Payroll sample data as a complement to the gold standard official statistics. Our indicators offer more timely snapshots that ultimately rely on official statistics for benchmarking. We center our discussion on the US series and extend discussion to relevant elements of the UK and Canadian data as needed in the relevant sections and appendices.

The paper proceeds as follows. Section 2 provides background. Section 3 describes the QuickBooks data and the official data sources used for calibration. Section 4 describes features of the QuickBooks data and contrasts it against official statistics. Section 5 explores the growth dynamics of businesses using the QuickBooks platform. Section 6 describes the methodology to construct the Index as well as some limitations. We discuss model parameter tuning, and out of sample performance during COVID-19. Section 7 introduces the QuickBooks Small Business Index and discusses findings relevant to the current period. Section 8 concludes.

2 Background

The last few years have seen an explosion of datasets describing business dynamics — the process of businesses entering, exiting, expanding, or contracting. These datasets provide important insights into the entrepreneurial process and job creation. We are learning about the decline in business dynamism, the rich heterogeneity of businesses and entrepreneurs, about the role small and particularly young businesses play in job creation, and the volatility of young and small businesses – the majority of these exit within the first few years but a few, the more innovative ones, grow to lead the new industries of the future (Haltiwanger, Jarmin, and Miranda, 2013; Haltiwanger et al., 2016; Sterk, Sedláček, and Pugsley, 2021; Akcigit et al., 2022). We have also learned that small and young businesses are particularly sensitive to shocks. These businesses are more likely to shed workers early in a recession and generate a disproportionate number of jobs early in the recovery (e.g., Fort et al., 2013; Pugsley and Șahin, 2019). These businesses are important for the pace of economic recovery. In this regard, young and small businesses are early indicators of economic activity and tell us something about the state of the economy (Asturias et al., 2021). Insights from these datasets are helping to shape the direction of research (Nagaraj and Tranchero, 2022).

These new datasets are made possible by the development and use of confidential administrative datasets by statistical agencies for statistical and research purposes. Administrative data are collected regularly using various administrative processes, typically at an annual or quarterly frequency. In the US the US Bureau of the Census and the Bureau of Labor Statistics have taken the lead in developing public use statistics aggregated from these types of confidential micro datasets.[7] Important examples are the Business Dynamics Statistics (BDS) derived from the confidential Longitudinal Business Database (LBD), and the Business Employment Dynamics (BED) derived from the Quarterly Census of Employment and Wages (QCEW). Administrative datasets have not only opened up new areas of research but Statistical Agencies recognize their unique value as benchmark indicators of economic activity and regularly update the existing public use series.[8]

An important element of what makes administrative data so valuable is that it covers the universe or near universe of the target population – in this case US businesses, regardless of size, age, industry, or location. Survey data is necessarily more limited in its ability to capture the rich heterogeneity of businesses regarding their characteristics or their performance. Not surprisingly, users of these data continue to request even more detail with each expansion.[9]

One area where policy makers are keen to see further development is in regards the timeliness of the data releases as well as their frequency — ideally monthly or weekly with as short a time lag from the time of the events as possible.[10] This is particularly challenging when working with administrative datasets since they take time to process. Additionally, collecting these types of data for the universe of firms at a higher frequency would be prohibitive. It is for this reason that agencies turn to small monthly surveys —- such as the Job Openings and Labor Turnover Series (JOLTS). These efforts by statistical agencies recognize the need to provide accurate and timely information. In all cases, these surveys require significant effort to collect and process and are released with considerable lag.[11]

Here we strive to use what is tantamount to administrative data from a private company, Intuit, to build an index of small business activity that captures the net job creation of small businesses. We start with the US and then expand to Canada, and the UK. Our goal is to create a Small Business Index that is as timely and accurate as possible. For this reason, we make use of the official administrative releases, including from the BED and JOLTS for the US, to discipline a new series built from these data. For the UK and Canada we use available survey data which is by design highly current. Our purpose here is purely illustrative at this time. Before we delve into the methods we describe the Bureau of Labor Statistics benchmark data we use in more detail.

[7]These agencies only release these datasets after a careful disclosure review process that ensures no confidential information is disclosed about particular businesses or individuals.

[8]Statistical agencies continue to work on and expand the types of data products derived from administrative data. A recent example is the release of the BDS High-Tech describing the dynamics of high-tech industries (Goldschlag and Miranda, 2020).

[9]The BDS is the prime example for this. It started as a basic dataset describing business dynamics, but over time the data has been expanded to include additional details including industry, geography, high-tech, or trading status. Other datasets are in the work including high growth and a higher frequency series.

[10]This was the impetus behind the creation of the Busines Formation Statistics (Bayard et al., 2018). This is the Bureau of the Census high frequency indicator of business formations. It is built from administrative data (applications for new EINs) to describe business formations in near real time.

[11]The US Census Bureau produces a series of indicators of economic activity, but these are released with considerable lag. See https://www.census.gov/economic-indicators/.

3 Data

In the construction of the QuickBooks Index for the US we make use of three data sources: the QBO Payroll sample (in accordance with Intuit's privacy-protective requirements), the Business Employment Dynamics (BED), and the Job Openings and Labor Turnover Series (JOLTS). Before turning to the Intuit microdata in Section 3.2 we briefly lay out the relevant features of the BED and JOLTS datasets in some detail. Appendix A describes the basic features of the official Canadian and UK data.

3.1 Benchmark Data of the US: BED and JOLTS

The BED is a set of statistics generated from the Quarterly Census of Employment and Wages (QCEW) program of the Bureau of Labor Statistics. A key feature of these quarterly data series is that it provides information on the number of business birth and deaths, and the number of jobs gained and the number of jobs lost from 1992 forward.[12] Importantly for our purposes these data are more timely and are released at a higher frequency than similar databases.[13]

Underlying the BED are the QCEW data. This is an administrative dataset obtained from reports of employment data for workers covered by Unemployment Insurance (UI) and Unemployment Compensation for Federal Employees systems. Employers are required to provide this information to comply with state unemployment insurance programs through State Employment Security Agencies (SESAs). All employers subject to state UI laws are required to submit quarterly reports detailing their employment and quarterly wages. This is a virtual census (98%) of employees on non-farm payroll. Because data are collected for the entire population of businesses, there are no sample estimates and the published data are not subject to sampling error. The BED statistics are created from a subset of records covered in the QCEW dataset. In particular, Government establishments are excluded, as are private households (NAICS 814110), and establishments with zero employment in two consecutive quarters. BED statistics also exclude establishments in Puerto Rico and the Virgin Islands. The exclusion of government establishments is appealing since QuickBook's data are limited to the private sector.

The BED program publishes national North American Industry Classification System (NAICS) sub-sector data, national firm-size data, state industry NAICS sector data, national industry NAICS sector data on establishment age and survival, and state data on establishment age and survival, as well as data on the size of employment change in establishments. We make use of the national firm-size data and target small businesses with between 1 and 9 employees.[14] Firm size

[12]Definitions for each of these concepts can be found on the BLS website: https://www.bls.gov/opub/hom/bdm/concepts.htm.

[13]The Business Dynamics Statistics provides statistics on gross job creation and destruction from entrants, exiters, and continuers on an annual basis.

[14]Firm-size data in BLS parlor refers to employer units. These are businesses tax units encompassing one or more establishments. An employer unit may or may not correspond to a firm, although for small firms the establishment, firm, and employer units coincide. A unique identifier assigned to each record allows tracking of each business across

classification is based on a dynamic sizing methodology.[15] Employment changes in the BED are measured from the third month of the previous quarter to the third month of the current quarter. All of the BED components — gross job gains and losses, are seasonally adjusted using the X-13-ARIMA program. The BLS maintains the additive properties of each series, gross job gains, and gross job losses by adding the seasonally adjusted expansions and openings components and the seasonally adjusted contractions and closings components.

The BED data are only available at a quarterly frequency, so we make use of the BLS Job Openings and Labor Turnover Series (JOLTS) to create a monthly frequency BED-JOLTS Composite (BJC) estimate of the BED series which we describe further below. The JOLTS produces monthly estimates of job openings, hires, and separations for the nation.[16] While the JOLTS concepts do not fully align with the BED, nonetheless it is possible to create a net job creation series from the sum of hires and separations that we use for our purposes.

The JOLTS sampling frame is primarily made up of establishments from the QCEW. It has a sample of approximately 21,000 units drawn randomly from a stratified sample. The JOLTS data are available by ownership (private versus public), region, supersector, and select industry sectors. For our purposes, we focus on private sector data which excludes government employment, and military personnel. The JOLTS also exclude sole proprietors, the unincorporated self-employed, unpaid volunteer or family workers, farm workers, and domestic workers. The private level estimates are produced by establishment size class. The JOLTS program also produces estimates for all 50 states and the District of Columbia. State estimates are produced monthly at the total nonfarm level.

Job openings include all positions that are open at the end of the reference month and could be filled in the following 30 days. Hires include all additions to the payroll during the entire reference month, regardless of hours worked or permanent/short-term, or seasonal status. Separations include all separations from the payroll during the entire reference month and are reported by type of separation: quits, layoffs and discharges, and other separations. For our purposes we use seasonally adjusted numbers produced by the BLS. We define net job creation for relevant size, industry, and regions as the difference between the hiring rate and the separation rate.

JOLTS defines size at time of sample selection as the maximum employment of the establishment over the last 12 months. This classification stays fixed for a year until the next annual sample is drawn. We focus on the smaller size class 1 to 9 where the difference between establishment and firm is minimized.

time despite changes in name or ownership.

[15]For a discussion of this methodology see Butani (2006).

[16]Definitions for these concepts can be found on the BLS website: https://www.bls.gov/opub/hom/jlt/concepts.htm.

3.2 Intuit QuickBooks Data

QuickBooks is an ecosystem for small businesses, offering accounting, payroll, payments, and time tracking applications. As of July 2022, Intuit served 7.1 million online paying small business customers, including 5.9 million QuickBooks Online subscribers. The larger base of subscribers is in the US, while the UK and Canada also have a sizable customer base. A portion of subscribers use QuickBooks Payroll to pay their workers and access human resources and benefits. We use a sample of the QuickBooks Online Payroll (QBO Payroll sample from now on) to create employment growth rates. The index uses payroll data from a sample of 333,000 businesses in the US, 66,000 in Canada, and 25,000 in the UK.

The administrative data for each payroll account corresponds to the firm and may also correspond to business establishments (physical locations where business is conducted). Payroll records are updated at the end of each pay period. The records consist of a longitudinal ID, the date payroll was processed, employment information for the pay period, hours worked, gross pay, taxes, bonuses/adjustments to pay, and furlough payments. Subscription join and cancel dates are also available. Company industry is self-reported as is the company's location (region is imputed from postal code if region is not reported). From this administrative data, we identify counts of workers, furloughed employees, and paychecks issued in a given pay period. Workers include wage earners with no hours in the pay period, workers on unpaid leave, and furloughed workers. We focus on active workers and exclude furloughed workers as well as bonus payments and adjustments. Throughout, we work with data processed by Intuit's data analytics team, following Intuit's Data Stewardship Principles, and in accordance with Intuit's Global Privacy Statement.

3.3 Sample Construction

3.3.1 Data Frame

Each month, Intuit analysts identify, from the total QuickBooks Online Payroll customer sample, a list of active subscribers. Next, Intuit analysts obtain the payroll activity records at the paycheck level for each subscriber. These data are then aggregated by segment (such as weekly or bi-weekly) and used to derive our metrics. In this paper we focus on the monthly frequency data and active workers excluding furloughed workers as these records are better behaved. We plan on exploring higher frequency and activity distinctions in the future.

3.3.2 Firm Size

We follow the average size methodology to define the size of a business (Davis, Haltiwanger, and Schuh, 1996, hereafter DHS). An establishment i belongs to size class s (defined by bounds s_l and

s_u number of employees) in period t if

$$\frac{E_{i,t} + E_{i,t-1}}{2} \in [s_l, s_u]$$

i.e., the size is determined by the average size of the two periods. We can then calculate the net employment gains conditional on the above condition for each size class.[17]

3.3.3 Industry Assignment

There are two industry codes available for the QBO Payroll sample: 1) self-reported values if these data are provided by the subscriber, 2) predicted using a classification algorithm based on transaction data when this item is missing.

We use a combination of self-reported and predicted values. About 40% of the firms on the QuickBooks platform provide a precise 6-digit NAICS industry code.[18] The rest are imputed to the 2 and 4-digit level using a TF-IDF text classification model using a variety of information including company name, URL information, invoices, and inventories.[19] We use the 2-digit industry classification where industries are classified with an f-1 score of over 0.5 in most instances.[20]

The industry-level sample differs from the regional-level and the economy-wide samples. For each segment breakdown, we exclude records that don't have industry or regional data.

3.3.4 Region Assignment

The region of a firm is assigned using the location provided by the account administrator. In case a user-provided location is not available, a region is imputed using the postal code of the firm's transaction activity.

4 QuickBooks Online Payroll (QBO Payroll) Sample Characteristics

For a nationally representative employment growth series, we need to account for the differences in the observable and unobservable characteristics of the QBO Payroll sample as compared to the national economy.

[17] This methodology has become standard in the literature. It provides symmetrical firm-size estimates and eliminates any systematic effects that might be caused by the transitory, changes in firms' sizes over time. For a treatment of reversion to the mean effects, see Davis, Haltiwanger, and Schuh (1996).

[18] This value is obtained from a self-reported dropdown menu. Percentage pertains to all QuickBooks sample and not just the QBO Payroll sample.

[19] TF-IDF (term frequency–inverse document frequency) is a numerical statistic that captures how important a word is to a document in a collection of documents. TF-IDF is one of the most popular classification and ranking methods.

[20] The f-1 score provides a measure of the accuracy of the prediction.

4.1 Sample Composition

The users within the QBO Payroll sample are significantly concentrated among small firms. The large amount of data allows us to focus on the smallest of small businesses; an activity segment that is particularly challenging to cover by other indices.[21]

We observe significant growth on the QuickBooks platform in both the number of businesses and the total employment, which is primarily driven by an increase in subscriptions over time. We find average employment size of firms in the Quickbooks' sample increases with business age consistent with learning by doing and selection dynamics noted in the literature and observed in official statistics. Exit rates are high among the smallest platform users consistent with those selection dynamics. Many firms find out they are not sufficiently productive and quickly exit, which is also consistent with official statistics. The large firms of the future originate in this large pool of small-young firms. In the QuickBooks platform, selection dynamics are confounded by platform use dynamics.

4.2 Region, and Industry Representation of the QBO Payroll Sample

We start this section by describing the US data. We then move to the UK and Canada data. For this section we focus on the small firm business sample including firms with 1 to 9 workers for the US and the UK and 1 to 19 workers for Canada since this is the focus of the index.

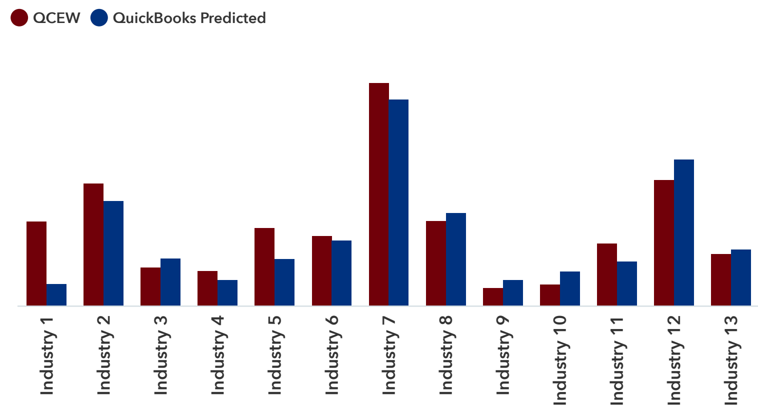
4.2.1 Intuit QuickBooks in the US

Figure 3 shows the industry composition of the QBO Payroll sample of firms as compared to the firms in the QCEW. Only selected industries are shown for confidentiality concerns. We find all sectors have wide support in the data with some variation in the sectoral distribution of the QBO Payroll sample relative to the official distribution for size class 1 to 9. Some industries (not shown) appear to be well over-represented in the QBO Payroll sample data.[22]

Figure 4 shows the regional distribution of the QBO Payroll sample of firms as compared to the firms in the QCEW. Only selected states are shown for confidentiality concerns. The QBO Payroll sample data presents similar regional variations compared to the official distribution of firms, with some notable exceptions.

[21] Our most recent annual sample is over 2.5 times that of the Current Employment Statistics (CES) sample used by the BLS to produce their national employment numbers, which is based on 131,000 businesses, and 15.8 times larger than the JOLTS sample of 21,000 establishments. The sample period for the US and Canada starts in January 2015, while the UK sample period begins in June 2016.

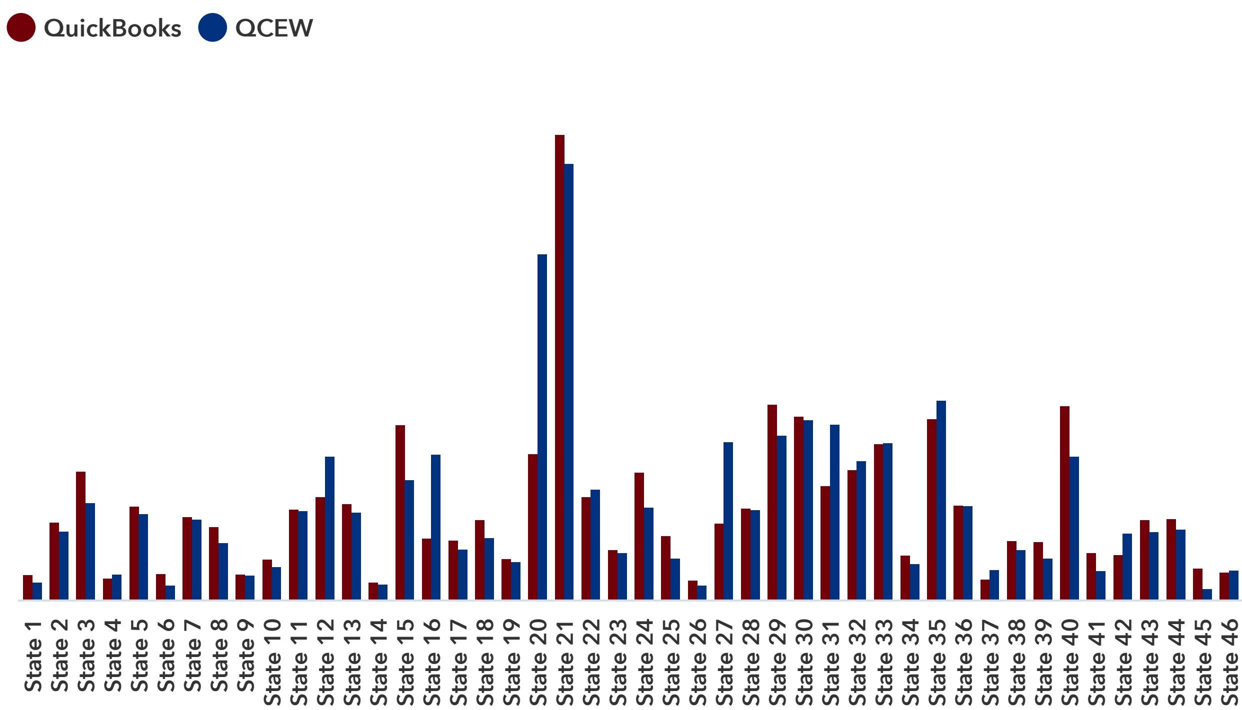
[22] We caution the reader to exercise appropriate care when interpreting these statistics given the imputed nature of much of the industry data.



Some industries and the y-axis are omitted from the figure because of confidentiality, but are used in the analysis.

Source: QCEW Size 1-9. First Quarter 2022. Total Establishments 8,812,930. QuickBooks March 2022 Predicted Industries, Total Establishments with known industry 308,915.

FIGURE 3: INDUSTRY COMPOSITION OF QCEW VS. QBO PAYROLL SAMPLE



The figure omits some states and the y-axis due to confidentiality concerns, but they are used in the analysis.
Source: QuickBooks Online Payroll Sample and QCEW March 2022.

FIGURE 4: REGIONAL COMPOSITION OF QCEW VS. QBO PAYROLL SAMPLE

4.2.2 QBO Payroll Sample in the UK and Canada

We can assess how representative the QBO Payroll sample data are relative to the UK business population by contrasting them against business population statistics from the Office for National Statistics (ONS). The Department for Business, Energy & Industrial Strategy releases Business

Population Estimates (BPE)1-19 and provides the only official estimate of the total number of private sector businesses and their associated employment at the beginning of each year. We focus on the population of businesses with 1 to 9 employees. Only selected industries are shown for confidentiality concerns. As was the case in the US some industries appear to be over-represented in the UK QBO Payroll sample of firms (Figure 5).[23]

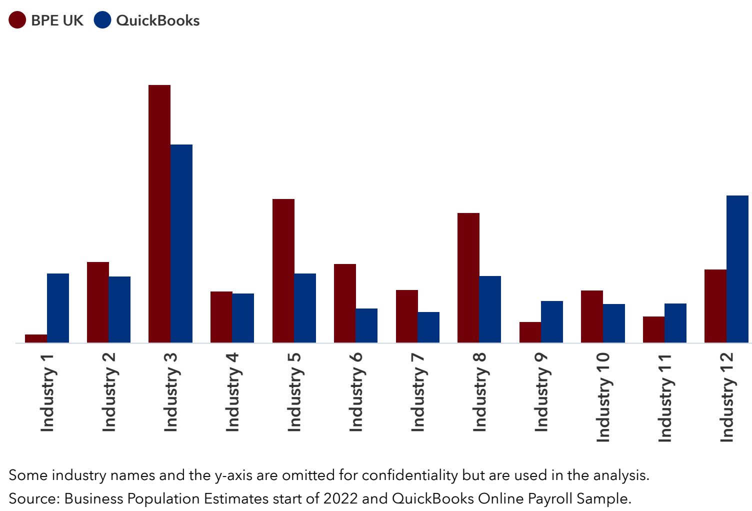


FIGURE 5: INDUSTRY COMPOSITION OF QUICKBOOKS UK VS. BUSINESS POPULATION ESTIMATES

We can similarly assess how Canada's QBO Payroll sample users compare relative to Canada's business population by contrasting against statistics from Stat Canada's Longitudinal Employment Analysis Program (LEAP). Figure 6 shows the industry composition (selected NAICS sectors) of the QBO Payroll sample firms as compared to the firms in Canada. As is the case in the US and the UK, while each industry has enough representation, the industry composition of QBO Payroll sample data differs from the official distribution in some industries.

Regarding the geographic distribution, users of QuickBooks platform are for the most part fairly equally distributed across the country with some variation across English and French speaking sections of the country (results not shown).

4.3 Other Sample Differences

In addition to the differences in the regional and industrial composition, we might expect the sample of the QuickBooks platform to be selected along other dimensions and to differ from the average small firm. Indeed, one might expect that small firms that use software products for managing their financial transactions and payroll activity might be better managed and technology savvy, more dynamic and/or higher productivity firms.

[23]When it comes to the geographic distribution, we find users of the QBO Payroll platform in the UK are fairly equally distributed across the country (results available upon request).

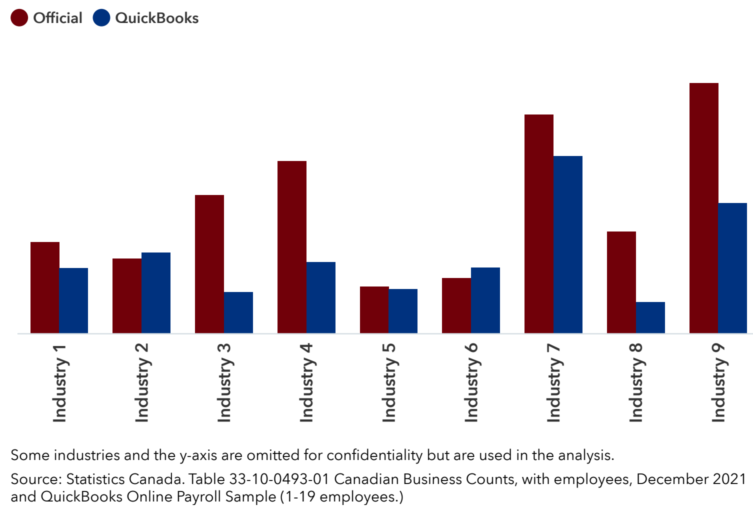


FIGURE 6: INDUSTRY COMPOSITION OF QUICKBOOKS CANADA VS. CANADIAN OFFICIAL STATISTICS

4.3.1 Small Business Software Usage - Survey Evidence

Not all firms use accounting or payroll software. Results from an Intuit QuickBooks study (Small Business Insights, September 2022) that surveyed 1,500 small firms (with less than 100 employees; 66% of the total sample had 10 employees or fewer) in the US show that only about half of the firms use any type of accounting software. The results also show that more than seventy percent of the firms still use spreadsheets and pen/paper to manage their transactions—sometimes alongside other systems (Figure 7).

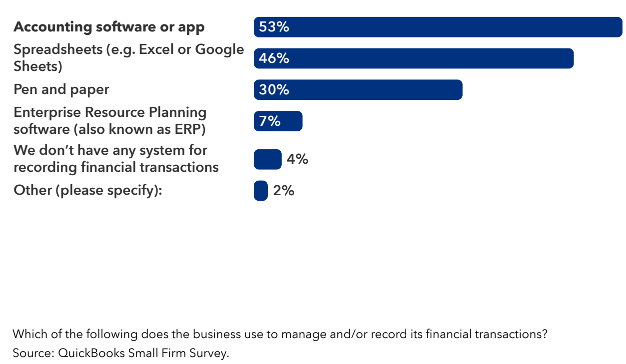


FIGURE 7: SOFTWARE USAGE

Firms that use accounting software or an Enterprise Resource Planning (ERP) program could be significantly different from the average small firms in the economy. They might have higher productivity/revenue due to better management practices. Or as firms grow larger and more productive, they might adopt technologies that they previously were not able to afford. Figures 8, 9, 10, and 11 show the survey results for Accounting Software and ERP tools usage by firm revenue.

These figures show a clear trend in technology adoption with firm revenue—the proportion of

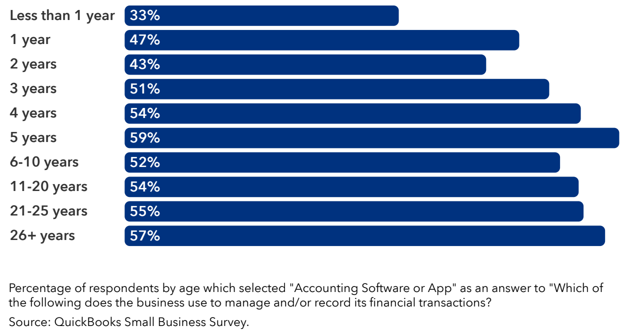


FIGURE 8: SOFTWARE USAGE BY FIRM AGE

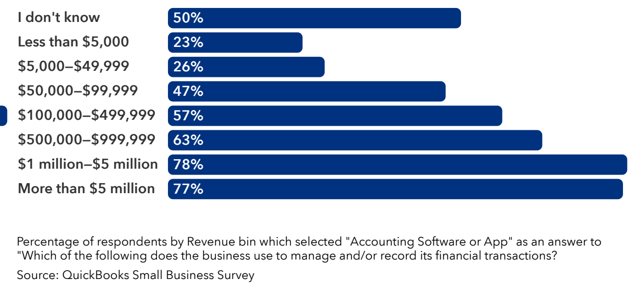


FIGURE 9: SOFTWARE USAGE BY REVENUE

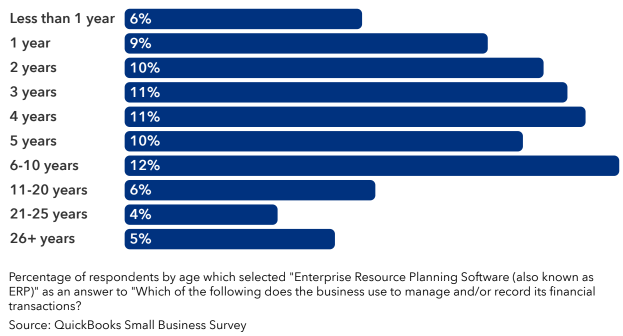


FIGURE 10: ERP USAGE BY FIRM AGE

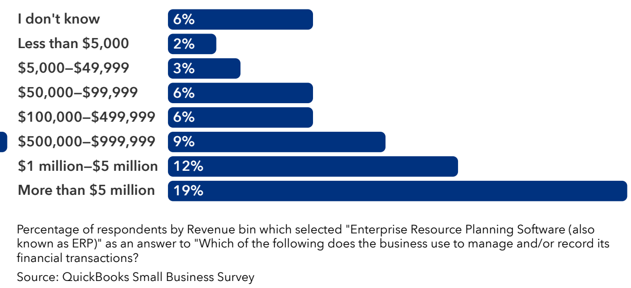


FIGURE 11: ERP USAGE BY REVENUE

the firms in the survey with any kind of accounting software or ERP tools growing with revenue. Use of accounting software such as Intuit QuickBooks also increases with business age; however, ERP usage follows a hump-shaped trend. This might suggest that older firms tend to be slower to adopt new technology as they age.

Figure 12 shows the proportion of survey respondents who use accounting software by their educational qualifications. The proportion increases with the educational level of the survey respondents.

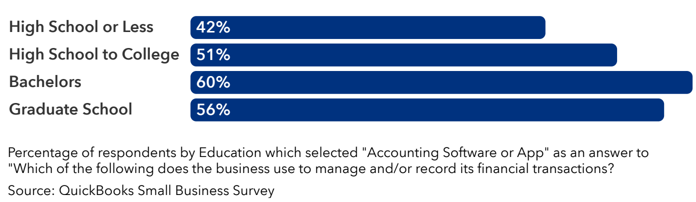


FIGURE 12: ACCOUNTING SOFTWARE USE BY OWNER EDUCATION

4.3.2 Discussion

The survey evidence presented in this section shows how firms that use accounting software such as QuickBooks might systematically differ from the average firms in the economy. These firms tend to have higher revenues, are relatively older, and are run by relatively more educated individuals. Re-weighting the sample to make it cross-sectionally representative of the small firms in the US population (by industry, size and geography) does not resolve the inherent bias in the QBO Payroll sample due to selection on characteristics unobserved in our data, such as the skill and productivity of the businesses and their owners. We note and recognize this fundamental difference and will explore ways to address it with the use of revenue data in the future. We further discuss sample selection issues in Section 5.4.2

5 Employment Growth Dynamics in QBO Payroll Sample Firms

In this section we describe basic features of the employment growth dynamics for small firms in the QBO Payroll sample. We compare key moments starting in 2015 against those from official statistics. For this section we focus exclusively on the US data. Appendix C provides similar analysis for firms in QBO Payroll Canada sample and QBO Payroll UK sample.

5.1 Employment Growth Rate

A worker is considered to be a part of the employment if the worker is on the payroll for the period t (which is a month in our case), and the business paid the worker at least once in that period.

Following Davis, Haltiwanger, and Schuh (1996) we define employment growth as the difference in employment in firm i between period t and $t-1$ divided by the average firm size as defined in subsection 3.3.2 as follows:

$$g_{i,t} = \frac{E_{i,t} - E_{i,t-1}}{0.5 \times (E_{i,t} + E_{i,t-1})} \tag{1}$$

Measuring growth rates in this manner yields an employment growth rate measure that is symmetric around zero and bounded between 2 and -2. It has become standard in the job flows literature.[24]

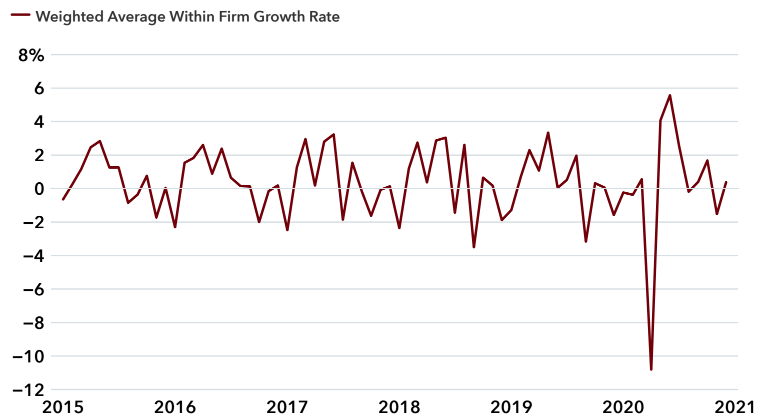
Using this firm level growth rate, we define two employment growth measures: 1) size-weighted within firm growth rate (excluding entry and exit) and 2) overall net employment growth rate as follows:

$$g_t^{\text{within}} = \frac{\sum_{i \in \mathbf{F}_t \cap \mathbf{F}_{t-1}} g_{i,t} s_{i,t}}{\sum_{i \in \mathbf{F}_t \cap \mathbf{F}_{t-1}} s_{it}} \qquad g_t^{\text{overall}} = \frac{\sum_{i \in \mathbf{F}_t \cup \mathbf{F}_{t-1}} (E_{i,t} - E_{i,t-1})}{0.5 \left(\sum_{i \in \mathbf{F}_t \cup \mathbf{F}_{t-1}} (E_{i,t} + E_{i,t-1}) \right)}$$

where $\mathbf{F}_t$ denotes the set of all the firms with non-zero employment in period t and $s_{i,t}$ is the size of the firm i. Figure 13 and Figure 14 plot the average within firm and the overall growth rates

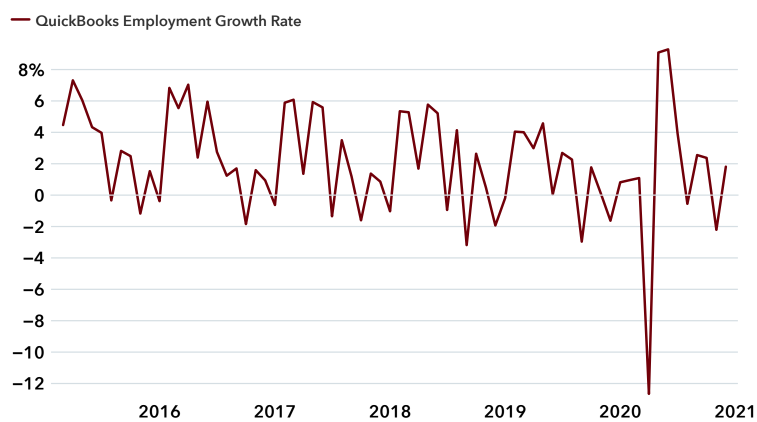
[24]See Davis, Haltiwanger, and Schuh (1998) for an extensive treatment of this measure. We note that the BED program uses a dynamic sizing methodology in its published statistics.

for the QuickBooks firms. We crop the series we display in 2021 for confidentiality reasons.



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: QuickBooks Online Payroll Sample.

Figure 13: Within Firm Growth Rate, g_t^{WITHIN}



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: QuickBooks Online Payroll Sample

Figure 14: Overall Growth Rate, g_t^{OVERALL}

First, note that both series are highly seasonal, with growth rates being highest around the middle of the year and then falling toward the end. Both series also capture the dip and the subsequent recovery in employment during the COVID-19 episode. The within-firm series captures the change only for firms which have positive employment in both the consecutive periods—thus abstracting for employment change due to entry and exit of firms. The overall series on the other hand, captures the entry and exit but these margins are confounded by the software usage patterns of firms (i.e., for an entrant, it could be the case that they are a newly born firm or they are an old employer but just started using the QuickBooks platform). Our data does not allow us to isolate employment growth from true entry and exit and the dynamics of subscriptions and cancellations in the QuickBooks platform. The within-firm growth rate on the other hand, will miss the firm entry/exit growth dynamics in the economy. The overall growth rate displays a much higher mean as compared to official data, as the QBO Payroll sample platform subscribers have been growing over time.

Note we can decompose the net overall employment growth rate into three components; growth from continuing firms, opening firms, and closing firms, i.e., the numerator in g_t^{overall} can be expressed as:

$$
\begin{aligned}
G^{\text{overall}}(t) &\equiv \sum_{i \in \mathbf{F}_t \cup \mathbf{F}_{t-1}} (E_{i,t} - E_{i,t-1}) \\
&= \underbrace{\sum_{i \in \mathbf{F}_t \cap \mathbf{F}_{t-1}} (E_{i,t} - E_{i,t-1})}_{\text{continuing firms}} + \underbrace{\sum_{i \in \mathbf{F}_t \setminus \mathbf{F}_{t-1}} (E_{i,t} - 0)}_{\text{opening firms}} + \underbrace{\sum_{i \in \mathbf{F}_{t-1} \setminus \mathbf{F}_t} (0 - E_{i,t})}_{\text{closing firms}}
\end{aligned}
$$

The first component can be further decomposed into expanding and contracting firms:

$$
\underbrace{\sum_{i \in \mathbf{F}_t \cap \mathbf{F}_{t-1}} (E_{i,t} - E_{i,t-1})}_{\text{continuing firms}} = \underbrace{\sum_{i \in \mathbf{F}_t \cap \mathbf{F}_{t-1}, E_{i,t} > E_{i,t-1}} (E_{i,t} - E_{i,t-1})}_{\text{expanding firms}} + \underbrace{\sum_{i \in \mathbf{F}_{t-1} \cap \mathbf{F}_t, E_{i,t} < E_{i,t-1}} (E_{i,t} - E_{i,t-1})}_{\text{contracting firms}}
$$

So, we finally have:

$$
\begin{aligned}
G^{\text{overall}}(t) &= \left\{ \begin{array}{c} \underbrace{\sum_{i \in \mathbf{F}_t \cap \mathbf{F}_{t-1}, E_{i,t} > E_{i,t-1}} (E_{i,t} - E_{i,t-1})}_{\text{expanding firms}} \quad + \quad \underbrace{\sum_{i \in \mathbf{F}_{t-1} \cap \mathbf{F}_t, E_{i,t} < E_{i,t-1}} (E_{i,t} - E_{i,t-1})}_{\text{contracting firms}} \\ \underbrace{\sum_{e \in \mathbf{F}_t \setminus \mathbf{F}_{t-1}} (E_{i,t} - 0)}_{\text{opening firms}} \quad + \quad \underbrace{\sum_{e \in \mathbf{F}_{t-1} \setminus \mathbf{F}_t} (0 - E_{i,t-1})}_{\text{closing firms}} \end{array} \right\} \\
&= G^{\text{expand}}(t) + G^{\text{contract}}(t) + G^{\text{open}}(t) + G^{\text{close}}(t)
\end{aligned}
$$

Dividing both sides of the above expression by $\frac{\sum_{i \in \mathbf{F}_t \cup \mathbf{F}_{t-1}} E_{i,t} + \sum_{i \in \mathbf{F}_t \cup \mathbf{F}_{t-1}} E_{i,t-1}}{2}$ we get the overall growth rate as

$$
g^{overall}(t) = g^{\text{expand}}(t) + g^{\text{contract}}(t) + g^{\text{open}}(t) + g^{\text{close}}(t)
$$

This decomposition is informative about the different margins of employment growth. Note that $g^{\text{open}}(t)$ and $g^{\text{close}}(t)$ contain growth coming from both new firms in the economy and new subscribers to the platform. These four components also incorporate different seasonality, and we use this decomposition in Section 5.3 to construct the seasonally adjusted overall growth rate.

5.2 Distribution and Variance of growth rates

Employment adjustments, at a monthly frequency, are rare among small firms. We find that for the smallest size category –firms with less than five employees; approximately eighty percent of the continuing firms have zero employment growth when compared to the previous month (Figure 15).[25]

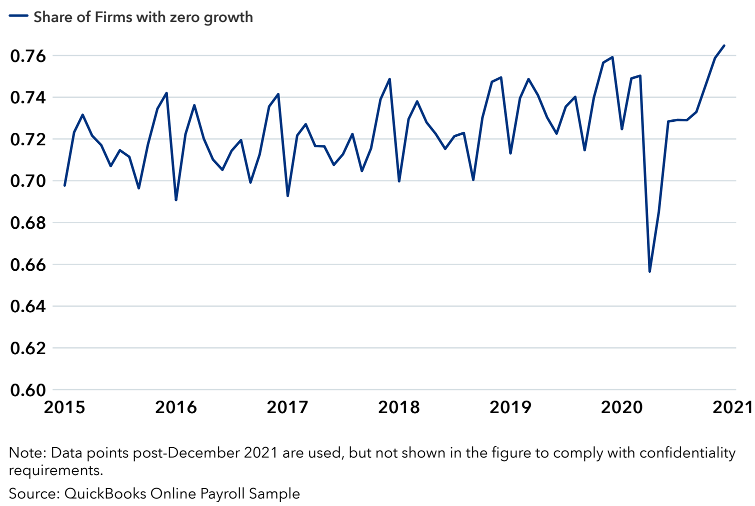


FIGURE 15: FIRMS IN SIZE 1–9 WITH ZERO GROWTH RATE.

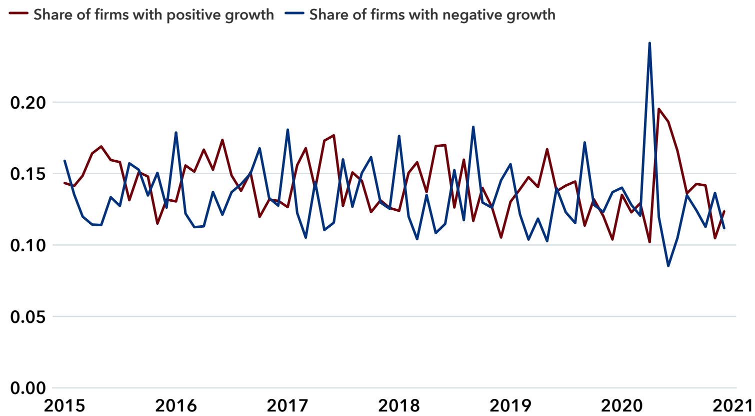
Figure 16 shows the share of firms with positive and negative growth rates on the platform. As can be seen this series is also highly seasonal. Platform subscription dynamics play a large role in entry/exit dynamics. Entry and exit dynamics explain to a large degree the seasonal variation observed in Figure 16 and lead to significant seasonal variation in the variance of growth rates; Figure 17.

We explore the mean variance of growth rates by firm size and firm age as defined by entry into the platform. We look at the full sample of firms between 2015 and 2022. We subset the sample into two firm size classes 1 to 4, and 5 to 9 in Figures 18 and 19, respectively. Growth dispersion declines with age in Census Bureau administrative data (Haltiwanger et al., 2016). We see the same patterns in the QBO Payroll sample with a high average growth rate for the youngest firms and declines in dispersion and average growth as firms age. These results are suggestive of learning by doing and selection effects widely discussed in the literature.

5.3 Seasonal Adjustment

To seasonally adjust the data, we follow the same methods and procedures followed by the BLS. First, we use the X-13-ARIMA SEATS program –specifically the R implementation of the pro-

[25] This is consistent with findings from the US Census Bureau Business Trends and Outlook Survey: https://www.census.gov/hfp/btos/data. They show that more than 80% of small firms (single establishment firms), do not change their employment at a biweekly frequency.



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.

Source: QuickBooks Online Payroll Sample

FIGURE 16: SHARE OF THE FIRMS WITH POSITIVE AND NEGATIVE GROWTH RATES EACH MONTH.

gram (seasonal library v1.9.0, x13binary v. 1.1.57-3). [26] The net growth rate series shows a simple seasonal pattern, but it masks different underlying seasonality on the entry, expansion, contraction, and exit margins. Appendix D shows the different seasonality patterns in the four series. Second, we adjust these margins separately and combine the seasonally adjusted components to obtain the final seasonally adjusted net growth rate series.[27]

Seasonal adjustment is performed on the level values, and then converted to rates with the seasonal adjusted job total series. Figures 20 and 21 show the different seasonally adjusted growth margins — job creation from openings and expansions (dark blue and light blue) and job destruction from closings and contractions (light gray and light green), for both the QuickBooks series and the BED respectively. The figures describe the patterns for firm size class 1-9 employees. The growth in platform use is again evident in the QBO Payroll sample, as is the impact of the COVID-19 shock on all margins, particularly contractions and closings initially followed by many openings and expansions. The BED series displays a flat pattern in general except for the COVID-19 shock in early 2020.

We retain the additive properties of the gross job gains and gross job losses by adding the seasonally adjusted expansions and openings components and the seasonally adjusted contractions and closings components. The seasonally adjusted net growth QuickBooks series is shown in Figure 22.

[26] We follow the same methodology for UK and Canada series.

[27] Seasonally adjusting the net growth rate series directly leads to a substantially more volatile series.

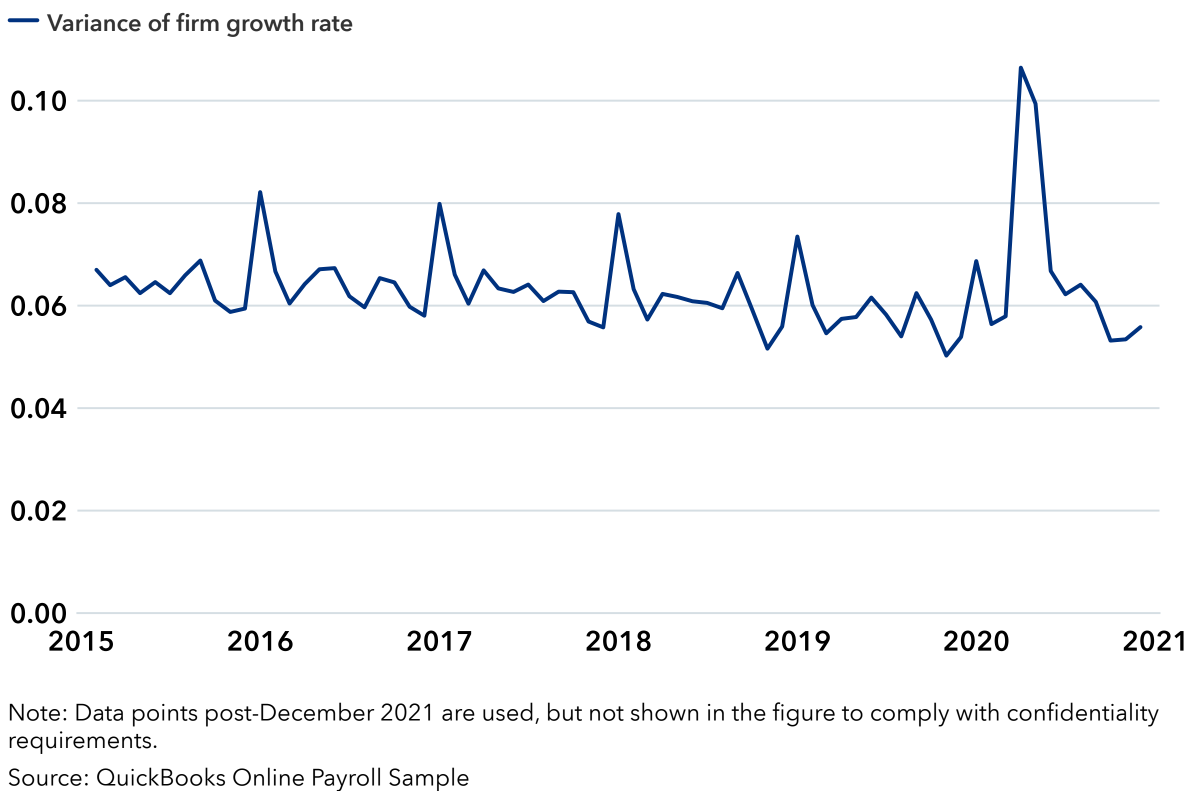


FIGURE 17: VARIANCE OF GROWTH RATES IN QUICKBOOKS

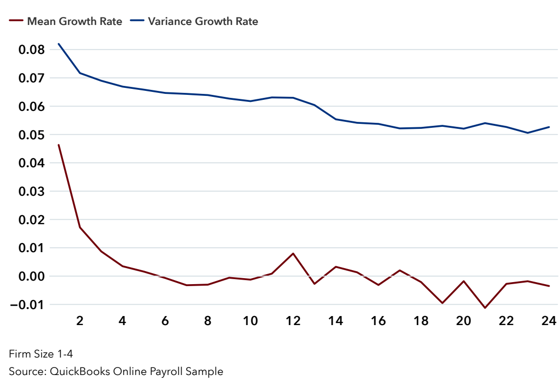


FIGURE 18: GROWTH RATES BY AGE (MONTHS)

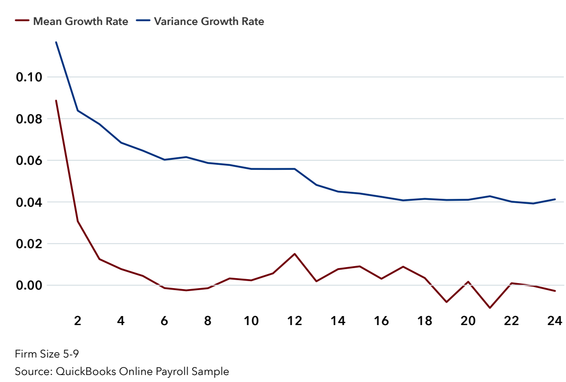
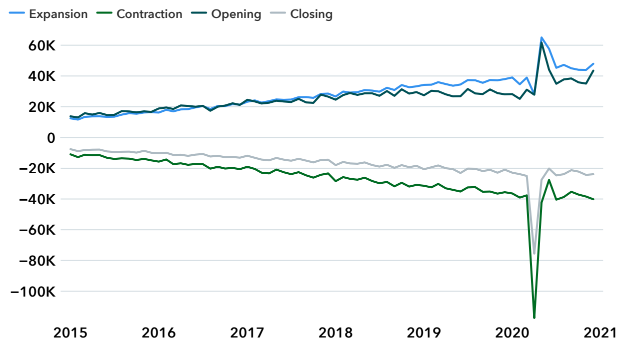


FIGURE 19: GROWTH RATES BY AGE (MONTHS)

5.4 Cross Sectional Heterogeneity and Re-weighting

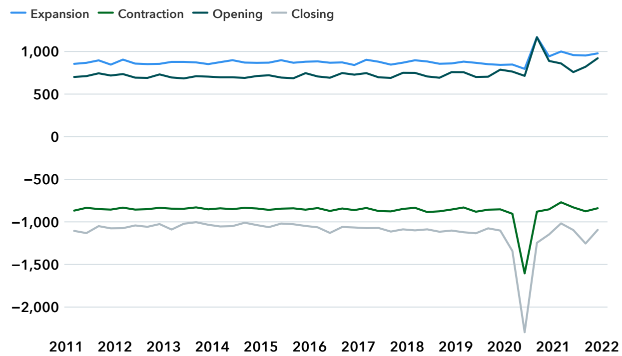
5.4.1 Regional and Sectoral Heterogeneity

Figures 23 and 24 show the seasonally adjusted growth rates for different sectors in the US. Pre-COVID-19, employment growth rates in different industries tend to co-move together. However, as widely studied, the impact of COVID-19 and its recovery has been significantly heterogeneous across different industries. QBO Payroll sample data captures this heterogeneity well. Industries such as 'Information, Professional, Scientific and Technical Services' or 'Finance, Insurance, Real



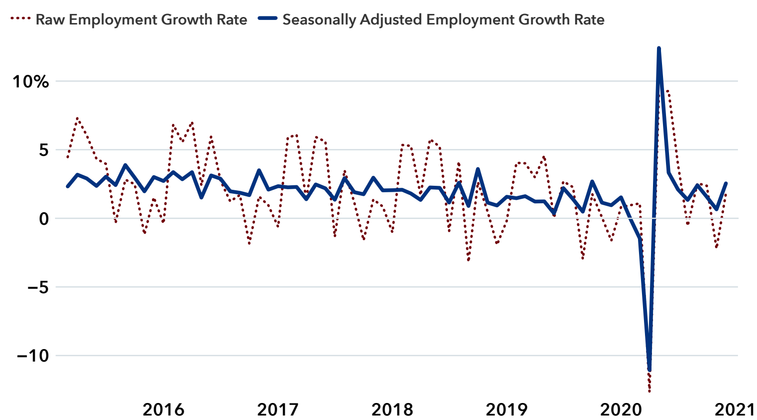
Firms Size 1-9, US. Note: Data points post December-2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: Seasonally Adjusted QuickBooks Online Payroll Sample.

FIGURE 20: SEASONALLY ADJUSTED GROWTH MARGINS, QUICKBOOKS SIZE CLASS 1 TO 9 (LEVELS.)



Employment gains (000's) for size class 1-9
Source: Business Employment Dynamics

FIGURE 21: SEASONALLY ADJUSTED GROWTH MARGINS, BED, SIZE CLASS 1 TO 9 (LEVELS.)



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: QuickBooks Online Payroll Sample.

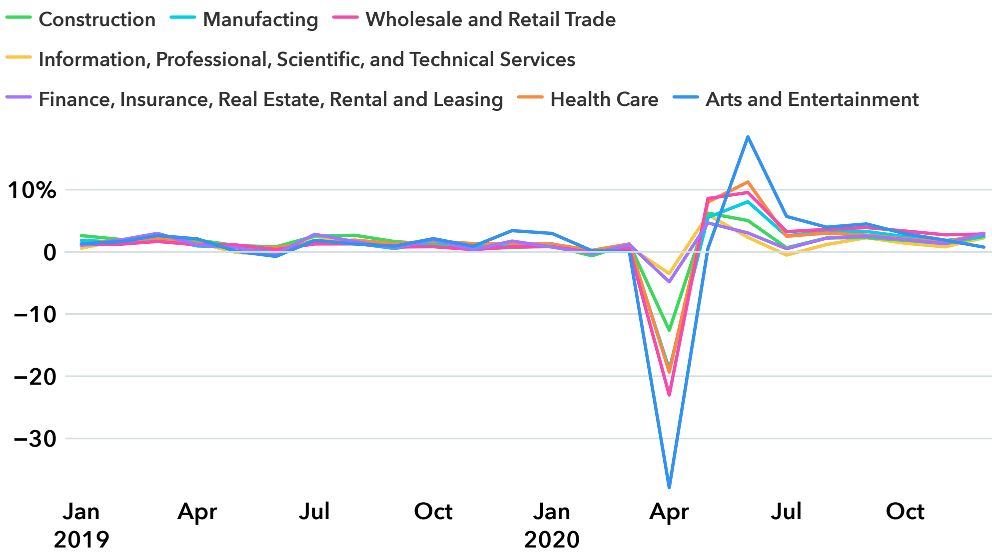
FIGURE 22: SEASONALLY ADJUSTED NET JOB GAINS

Estate, Rental and Leasing' had quantitatively small drops during COVID-19 and have been relatively stable since. On the other hand, industries such as Construction, Arts/Entertainment (Figure 23) saw significant contraction during COVID-19 but have had a strong growth in the recovery period. Accommodation and Food Services (Figure 24) saw the largest swing in COVID-19.

Figure 25 shows growth rates by region. Though there is some amount of heterogeneity among the regions, it is not as pronounced as between the sectors in US.

5.4.2 Cross-Sectional Re-weighting

As the employment growth rates for different industries tend to have different impacts during crisis, such as COVID-19, not accounting for their composition in the QBO Payroll sample data might give results which are not representative of the national economy.



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: Seasonally Adjusted QuickBooks Online Payroll Sample.

FIGURE 23: SEASONALLY ADJUSTED GROWTH RATES BY SECTOR

Let s denote the sector (and $\mathcal{S}$ be the set of all the sectors) and let $\Omega^s_{\text{QuickBooks}}(t)$ denote the total number of firms in sector s in period t for the QuickBooks data. And $\Omega^s_{\text{bench}}(t)$ be the corresponding number for the official benchmark data. So, for each sector, we can define the weight as

$$\omega^s(t) = \frac{\Omega^s_{\text{bench}}(t)}{\Omega^s_{\text{QuickBooks}}(t)}$$

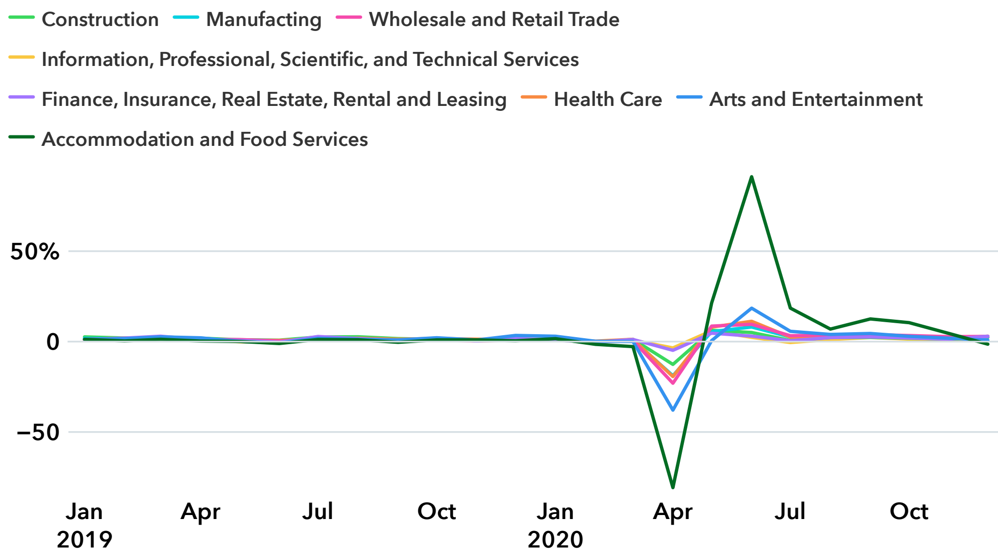
Let $g^s(t)$ be the growth rates for different sectors as plotted in Figure 23 and 24, then the overall growth rate could be expressed as

$$g^{\text{overall}}(t) = \frac{\sum_{s\in\mathcal{S}} \Omega^s_{\text{QuickBooks}}(t) g^s(t)}{\sum_{s\in\mathcal{S}} \Omega^s_{\text{QuickBooks}}(t)}$$

and we define the re-weighted series as

$$g^{\text{reweighted}}(t) = \frac{\sum_{s\in\mathcal{S}} \omega^s(t)\Omega^s_{\text{QuickBooks}}(t) g^s(t)}{\sum_{s\in\mathcal{S}} \omega^s(t)\Omega^s_{\text{QuickBooks}}(t)} \tag{2}$$

$\Omega^S_{QuickBooks}(t), \forall s \in \mathcal{S}, \forall t$ i.e. the sectoral composition of the QBO Payroll sample is available to us



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.

Source: Seasonally Adjusted QuickBooks Online Payroll Sample.

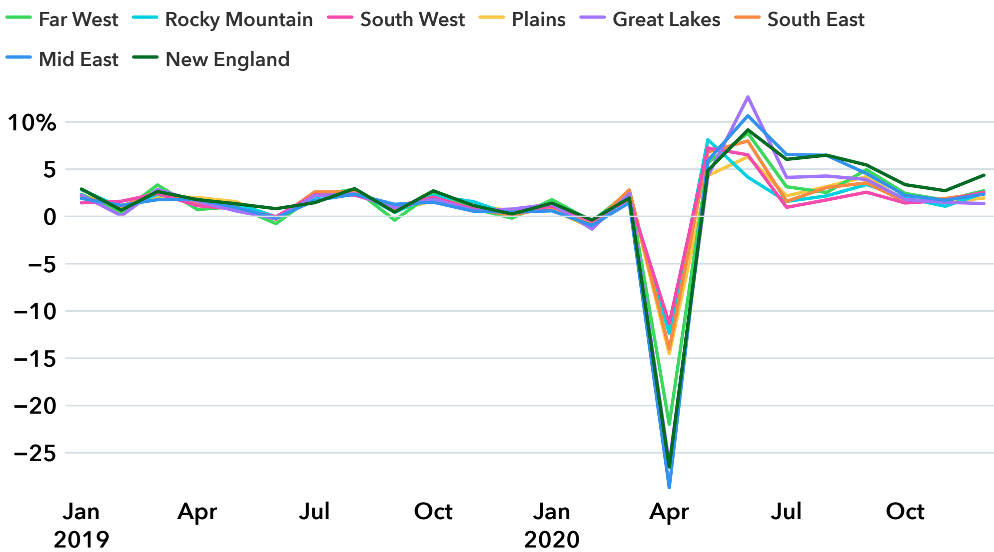
Figure 24: Seasonally adjusted growth rates by sector (Accommodation and Food Services in addition to sectors in Figure 23)

each month. However, QCEW establishment distribution by size and industry—our measure of the US sectoral composition ($\Omega^s_{\text{bench}}(t)$)—is only available for the first quarter of each year. Moreover, this is released with a lag of four months and the data is only available around August of each year. So, to calculate the weights $\omega^s(t)$, we use the current QBO Payroll sample distribution but update the benchmark distribution only every August. As the sectoral composition of the establishments in the whole economy tends to be stable over a short period, this does not limit our results.

Applying these weights and calculating the re-weighted growth rate as Equation 2 gives the final growth rate plotted in Figure 26. This is almost identical to the un-weighted g^{overall} series apart from a 2 percentage point difference during the COVID-19 drop in March 2020. Creating weights to adjust for geographic variation yields similar results. Given our findings, we proceed without any formal reweighing of the data at the national level. We thus rely on the calibration of the model for compositional adjustments.

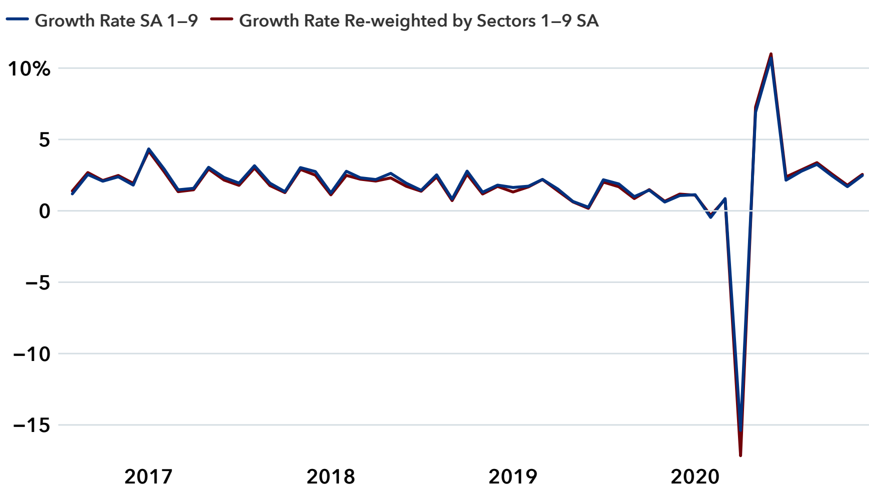
5.5 Benchmarking QBO Payroll Sample Data

In this section, we first compare the growth rate patterns in QBO Payroll sample data against official statistics. We compare first against the JOLTS — a monthly frequency survey-based indicator of small business activity, and the BED — the benchmark series indicator constructed from the full administrative data. The higher JOLTS frequency is ideal for our purposes; however, drawbacks include higher volatility, modeled birth/deaths, and a post production adjustment to



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: QuickBooks Online Payroll Sample

Figure 25: Seasonally adjusted growth rates by Region



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: QuickBooks Online Payroll Sample

Figure 26: Re-weighted Series

line up with the national CES statistics. The BED is the benchmark series we would like to target, but it is available only at a quarterly frequency. We create a composite JOLTS-BED series that combines the benefits of both JOLTS and BED. Our purpose is to find/estimate a feasible set of coefficients to adjust the levels of the QuickBooks series, so the resulting index will match to those of chosen official benchmark series. We use the composite series we create as our benchmark. The resulting series will be our aggregate Intuit QuickBooks Small Business series. We describe the steps we take to bridge them.

5.5.1 Comparing the QuickBooks Series to JOLTS

Figure 27 and Figure 28 compare the two seasonally adjusted QuickBooks series — the overall net employment growth series, and the series excluding entry and exit (continuers only), against the official JOLTS data.[28] A few observations are in order. First, note there is a good degree of co-movement between the two series. Especially the job losses and subsequent recovery around COVID-19 are almost perfectly captured by the QuickBooks series. Second, even after correcting for the seasonal platform use patterns, the overall QuickBooks series has a considerably higher growth rate when compared to JOLTS. As discussed earlier, this is due to the fact that the QuickBooks platform has been growing over time and thus the growth rate captures in part subscriber growth and not actual employment growth in the economy. The platform dynamics are also evident in the magnitudes of job losses and gains around COVID-19, where the growth rates are significantly higher in QuickBooks series compared to the official data. A number of establishments could have rather cut on their costs by leaving the platform, which gets captured as a job loss in this series. Third, the within-firm growth rate series abstracts away from entry and exit and therefore displays a significantly lower growth rate.

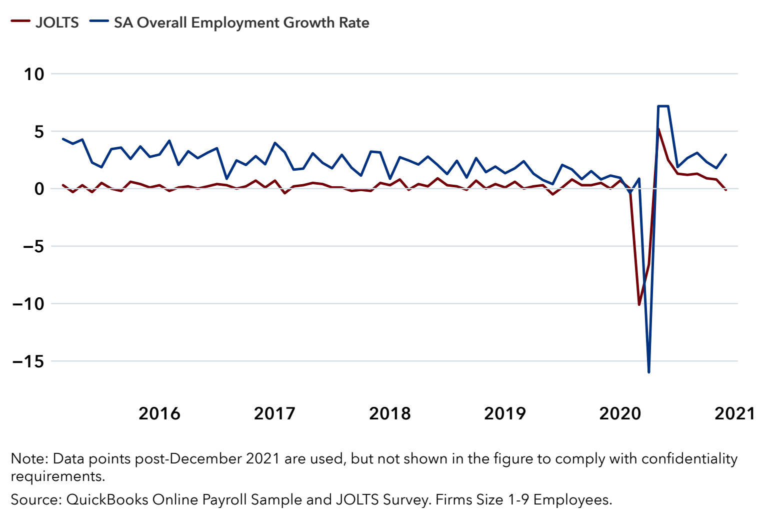


Figure 27: QuickBooks Seasonally-adjusted Overall vs. JOLTS

The JOLTS data as it is collected, on the other hand, also does not capture the establishments' births and deaths in a timely manner. This stems from the fact that it uses the QCEW as its sampling frame and there is almost a year's lag between a firm's birth and its eventual inclusion in the QCEW. Moreover, many small firms do not survive in their initial year of operation and thus do not make it into the sample. To account for this, JOLTS uses a Birth-Death model based on historical QCEW data and projected forward to the present using over-the-year changes in Current Employment Statistics. Unfortunately, the birth-death model currently in use by the BLS

[28] The details of the growth rate calculations are provided in Section 5.1.

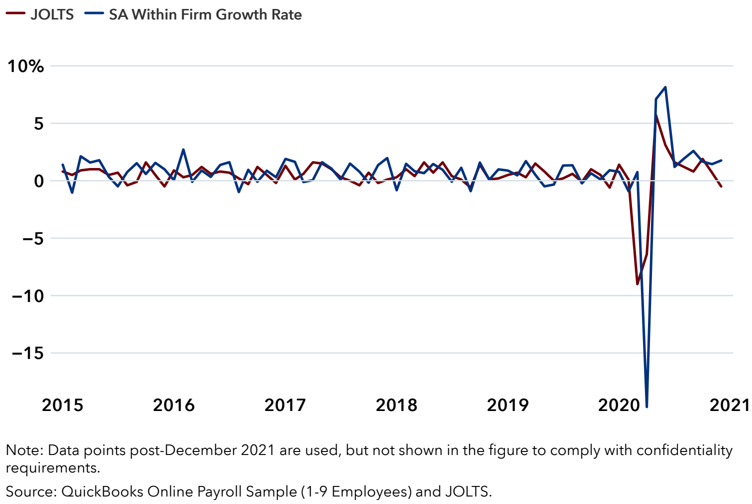


Figure 28: QuickBooks Seasonally-adjusted Within Firm vs. JOLTS 1–9.

fails to correctly capture growth dynamics from the opening and closing of establishments (Davis et al., 2010). This leads to a significant drift between JOLTS and BED. To account for this, the BLS performs an alignment with CES to correct for that drift. To see this, consider Figure 29 which shows the total employment levels in BED and JOLTS for the overall economy. The close match between the two series is quite apparent.

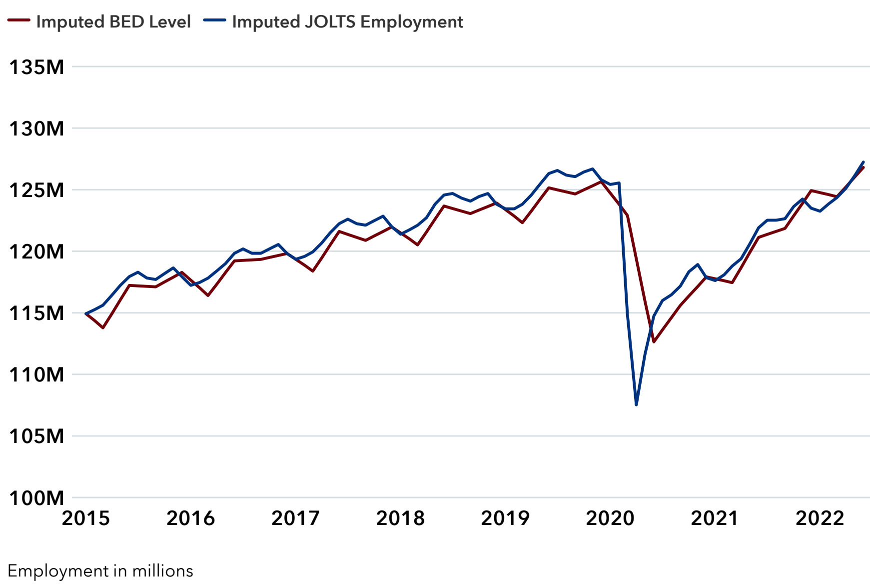


Figure 29: Total Employment: JOLTS/BED*, Nation

NOTES: BED and JOLTS are benchmarked against the QCEW starting in 2015. Monthly JOLTS data are aggregated quarterly. Data are not seasonally adjusted. Source data: Bureau of Labor Statistics.

On the other hand, Figure 30, repeats the same plot with firms that have at most nine workers. The drift here is significant. The BLS alignment works well for the nation as a whole. However, it does not correct the drift inherent to the birth/death model that affects primarily the small business segment we are interested in. The higher volatility inherent to sampled statistics in combination with the drift caused by the birth/death model results in an excessive growth implied by the net flow of hires and separations for small business in JOLTS when compared to the national benchmarks including the Current Establishment Statistics (CES) or the BED.[29]

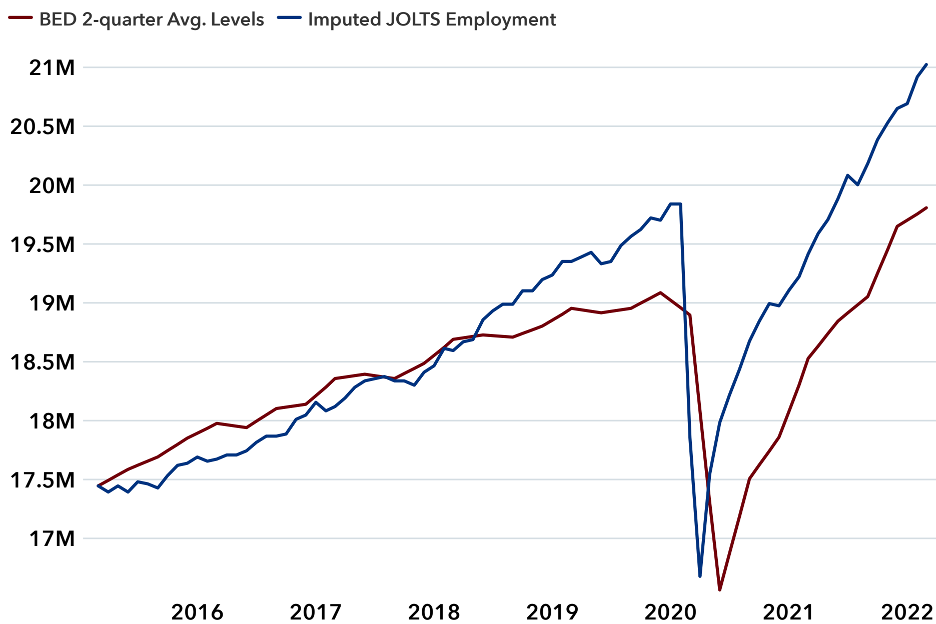


Figure 30: Total Employment: JOLTS/BED, 1-9 Workers

NOTES: BED and JOLTS are benchmarked against QCEW 2018 Q1.

As the QBO Payroll sample data is a near real-time[30] measure of the payroll and firm activity, it contains useful information about the rates of entry and exit of highly dynamic small firms in the economy. It can also capture firms which might not necessarily last long enough to be ultimately included in the official statistics and thus can provide a timely measure of economic activity in the small business sector. This, as noted earlier, is confounded by the entry-exit dynamics into the platform in contrast with actual entry and exit. However, as some of these firms might be new firms or the firms which are closing operations, removing them completely would understate the employment churn in the economy. In the next sections, we develop methodologies to isolate these trends. Even though the details are explained later, for the sake of comparison, we plot the resulting employment series from our index in Figure 31.

5.5.2 Comparing the QuickBooks Series to BED and BED-JOLTS Composite

Our purpose is to find/estimate a feasible set of coefficients to adjust the levels of the QuickBooks series, so the resulting index will match to those of chosen official benchmark series (Figure 32). The resulting series will be our aggregate Intuit QuickBooks Small Business series.

[29]See Davis et al. (2010) for an extensive treatment of these issues. Also see the JOLTS Birth-Death model.
[30]Near real-time refers to actual pulls of information, not a live data feed.

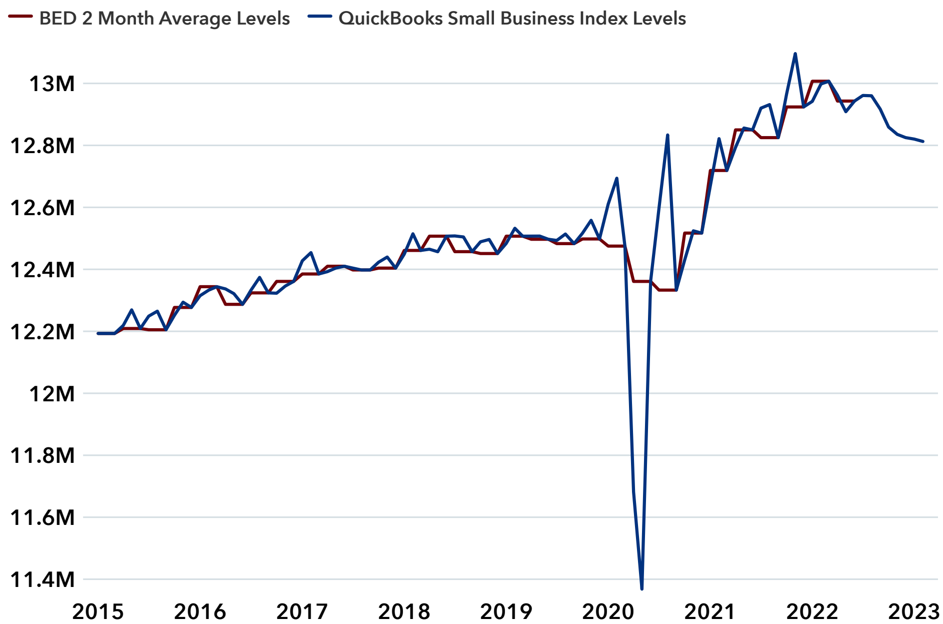


Figure 31: Total Employment: QuickBooks/BED*, 1–9 Workers

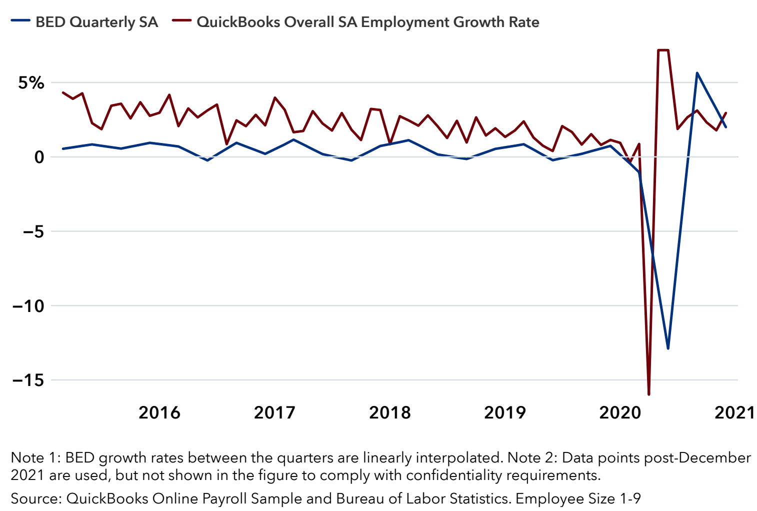


Figure 32: Quarterly BED vs. Monthly QuickBooks, net job creation rate, SA, percent

Our starting point is the BED data, our primary choice of benchmark series for the US. The series are published quarterly from administrative data and are considered the most reliable employment indicator including job expansion and contraction from continuers, as well as job creation and destruction from entrants and exits, including from very young establishments. Ideally, we would like to work with a higher frequency BED data series that is as timely as possible — the BED are produced with a lag of at least six months. We combine the quarterly BED data with the monthly JOLTS data to create a higher frequency "composite" BED series that has some of the features of the JOLTS but is constrained by the BED growth series.[31] The JOLTS

[31]This is similar in spirit to Davis et al. (2010). These authors develop and implement a method for adjusting the

are released in monthly frequency with less than a two-month lag.

Before turning to a description of our method, it is important to recognize there are important conceptual differences between the BED and JOLTS. To wit, the JOLTS is the result of a survey collection. Surveyed firms are asked to provide the number of job openings, hires, and separations during the reference month. These include all additions or separations to the payroll during the entire month. By contrast, the BED computes expansions and contractions from the difference in the number of jobs between the previous and current quarters. This naturally leads to a timing difference. Figure 33 displays the net job creation series from both the JOLTS and the BED series. It is apparent the BED captures the effect of the COVID-19 shock with a lag since expansions and contractions are only identified from the comparison of total employment between two lower frequency reference periods.[32]

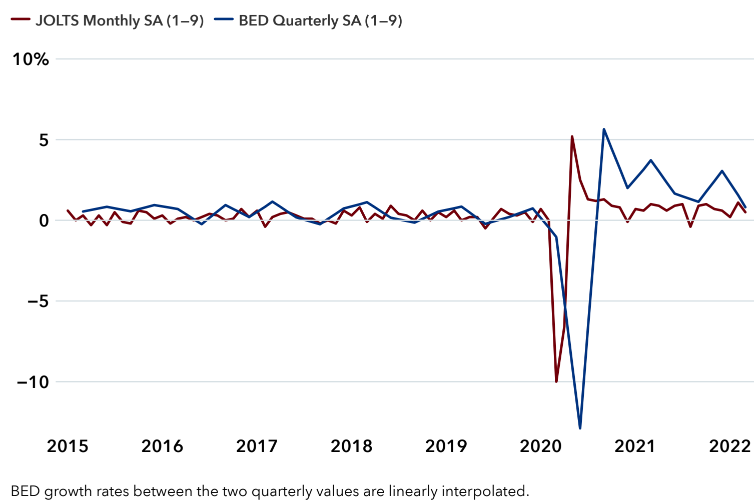


Figure 33: Quarterly BED vs Monthly JOLTS, net job creation rate, SA, percent

5.5.3 Frequency Conversion

Our official targeted benchmark, the BED data, and the QuickBooks user data need not be at the same frequency. When higher frequency data is not available, we apply a frequency conversion (or temporal disaggregation) technique to approximate or estimate the monthly observations.[33] Currently, we use a regression-based interpolation method proposed by Chow and Lin (1971) to handle the conversion of quarterly data to monthly frequency.[34] The Chow-Lin method allows

published JOLTS estimates to more accurately reflect worker flows and job openings in the US economy. They do so by matching the growth rate densities in JOLTS to the growth rate densities in the official BED series. Their method made use of the confidential establishment-level micro data. Unfortunately, their method has not been implemented in the production of the official JOLTS statistics. The confidential micro data is currently not accessible to us.

[32]Note the timing discrepancy would not be fully resolved even if we had a higher frequency monthly BED series. This is because job destruction in the BED is only identified from contrast with the following period's payroll.

[33]Since we are using monthly official series as benchmark for Canada and the U.K., we do not need to use conversion.

[34]We have also tried other methods proposed by Fernandez (1981), Litterman (1983), and Denton (1971), but the out-of-sample forecast performance was better for Chow and Lin (1971) in our case.

for higher frequency data to provide additional information to guide the model. In our case we use the JOLTS data discussed above as follows:

$$y_{j,t}^{BED,\ m} = \beta_j * y_{j,t}^{JOLTS,\ m} + u_{j,t}$$

$$u_{j,t} = \rho_j *\ u_{j,t-1} + e_t,\ \ 0 \le \rho_j < 1,\ \ e_t \sim\ IID(0,\sigma)$$

$$y_{j,t}^{BED,\ q} = \sum_{s=0}^{r-1} y_{j,t-s}^{BED,\ m},\ \ t = r,\ 3r,\ 6r,\ ...$$

The method finds an interpolated monthly frequency BED-JOLTS Composite (BJC) series, $y_{j,t}^{BED,\ m}$, for each size class, j, by relating the higher-frequency indicator series $y_{j,t}^{JOLTS,\ m}$ to a lower-frequency benchmark series $y_{j,t}^{BED,\ q}$ through the equations above. Errors, $u_{j,t}$, are assumed to follow an AR(1) model and the sum of three months interpolated within a quarter is constrained to be equal to the official BED value for that quarter. The results of the interpolation procedure can be seen in Figure 34. The monthly JOLTS data allows us to interpolate a higher frequency BED data from the relationship between the BED and the JOLTS series. The constraining effects of the BED benchmark data are obvious in that it doesn't fully resolve the lag inherent in the BED data.

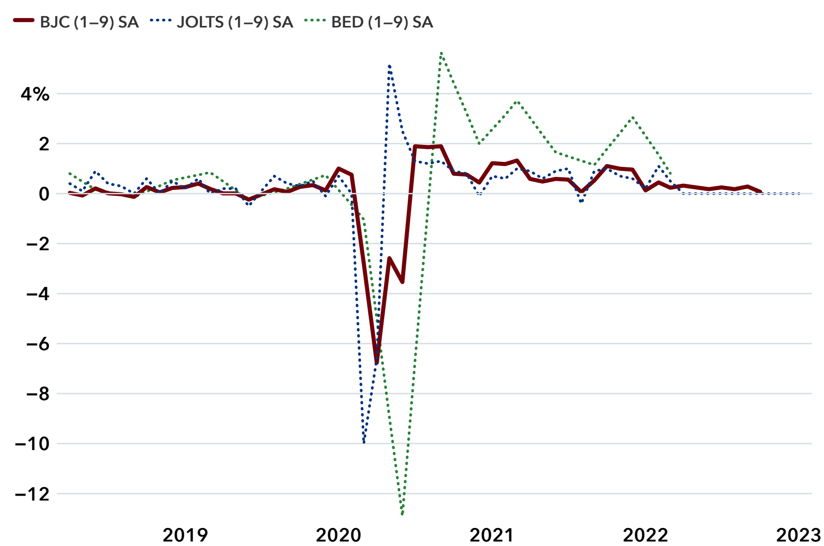
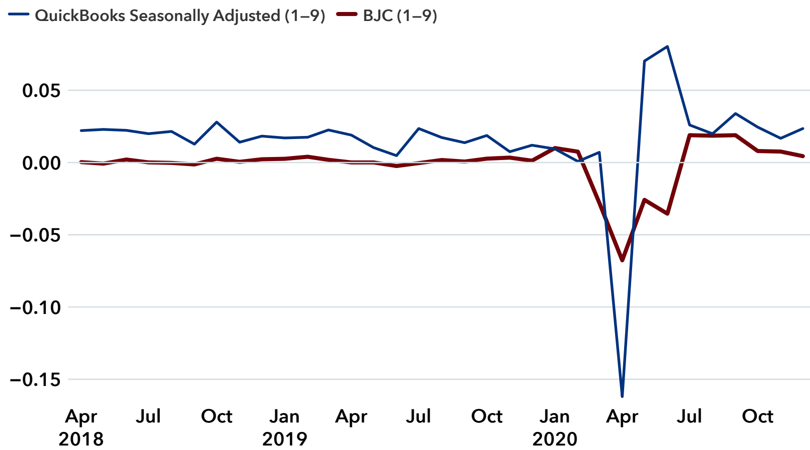


Figure 34: JOLTS and BED-JOLTS Composite (BJC)

This method allows us to use the JOLTS series as an indicator variable to interpolate the monthly changes for the quarterly BED series.[35] Figure 35 compares the resulting BJC series with QuickBooks, and shows that there is still some gap between the two. The next section describes the statistical model that we use to bridge that gap between QuickBooks and BJC.

[35]It has the additional benefit that it can extend the benchmark data beyond its official end date up to 8 or 9 months (at least two quarters) as the monthly JOLTS data is significantly more up to date within the constraints of the parameter estimates, the β_j. While possible we don't use available future JOLTS observations to extrapolate for the

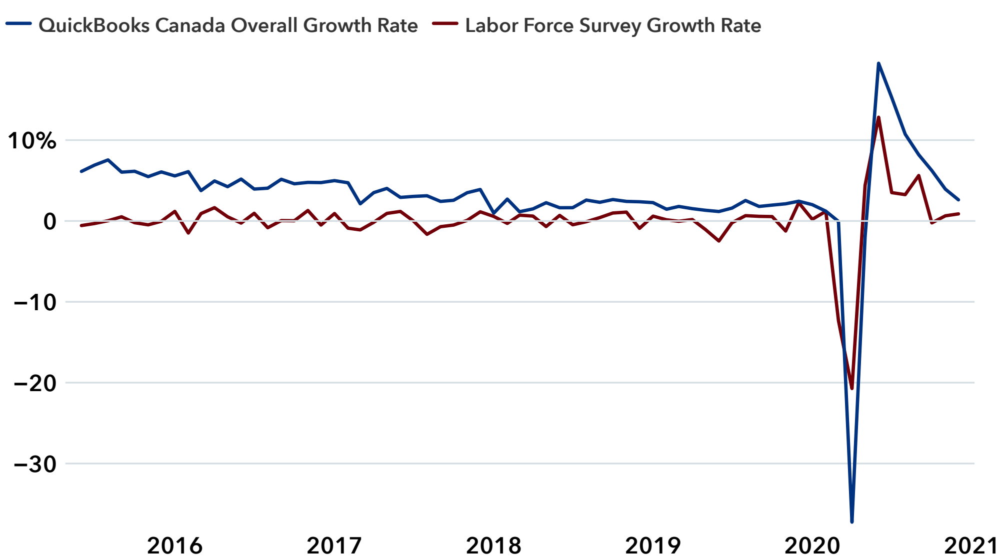


Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: Business Employment Dynamics, JOLTS and QuickBooks Online Payroll Sample.

Figure 35: QuickBooks Overall and BED-JOLTS Composite (BJC)

5.5.4 Comparing the QuickBooks Series to Official Series: Canada and UK

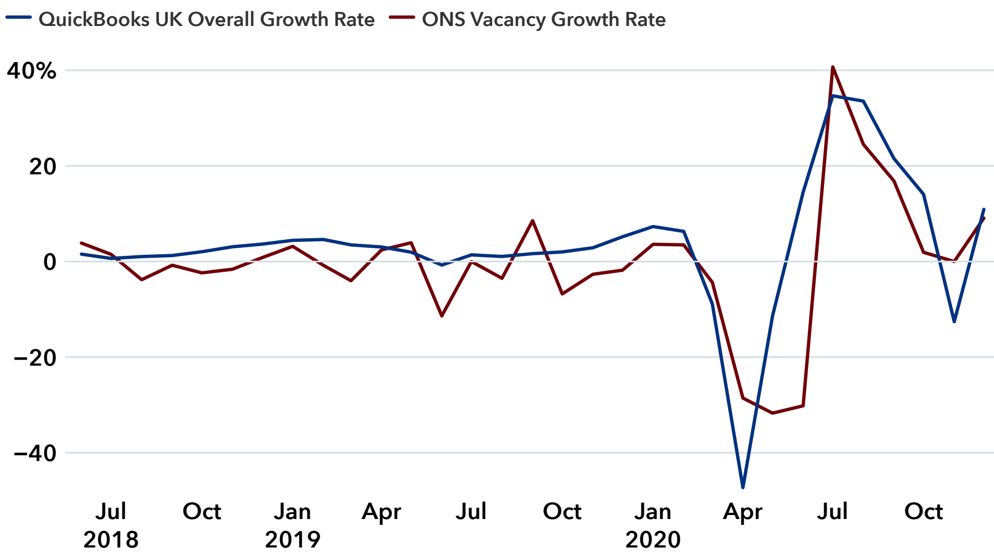
Fig. 36 and 37 shows the QuickBooks overall employment growth rates against the official employment growth rate and vacancy series in Canada and UK respectively. These series exhibit similar patterns as in the US with higher growth rates in general (due to platform growth) but track the official statistics well.



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: QuickBooks Online Payroll Sample and Labor Force Survey Canada for firm size 1-19 employees.

Figure 36: Canada QuickBooks Overall (without FLS) and Official Growth Rates

missing BED data.



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.
Source: QuickBooks UK Online Payroll Sample and ONS Vacancy Survey for firm size 1-9 employees.

Figure 37: UK QuickBooks Overall (without FLS) and Official Vacancy Growth Rates

We turn our attention to developing a flexible method to calibrate the QuickBooks series against the official series for the US, Canada, and the UK next.

6 Methodology

In this section we propose a method to model the relationship between the QuickBooks series and the BJC series that will serve to build our final Intuit QuickBooks Small Business series. We discuss the model in the context of the US data and discuss results and adjustments for the UK and Canada in Appendix A.

6.1 Flexible Least Squares

We follow a flexible least squares (FLS) approach to model the relationship between the QuickBooks series and the BJC series that will serve to build our final Intuit QuickBooks Small Business Index series.

Standard regression assumes that the parameters of the model do not vary across observations. However, this assumption may not hold due to possible structural changes or shocks occurring during the sample period. We then look for a model that incorporates as much historical data as possible and also uses recent observations more heavily. We begin by identifying the optimal lag structure for our base model (i.e., OLS) using "Least Absolute Shrinkage and Selection Operator" (LASSO) regression techniques. We start with a twelve-month lag structure but find that a second-order lag is optimal (see Appendix E).[36] To allow coefficients from our regression to change over time, we make use of a more flexible version of least squares analysis developed by Kalaba and Tesfatsion (1989):

$$\underset{\beta_{j,t}\in\mathbf{B_t}}{\operatorname{argmin}} R(\mathbf{B_t}) \ = \sum_{t=1}^{T}\left(y_t^{BED,\ m} - \beta_{0t} - \sum_{j=0}^{q} y_{t-j}^{INTUIT,\ m}\beta_{j+1,t}\right)^2 + \lambda \sum_{t=1}^{T}\sum_{j=0}^{q} d_j * \left(\beta_{j+1,t} - \beta_{j+1,t-1}\right)^2$$

where,

$$d_j = \sum_{t=1}^{T}\left(y_{t-j}^{INTUIT,m}\right)^2.$$

Here, q is the number of lags of our QuickBooks series that are used as explanatory variables. λ is a smoothing parameter, which denotes the inverse of signal-to-noise ratio. The larger (smaller) the lambda, the lower (higher) the signal-to-noise ratio. In other words, increasing (decreasing) the value of lambda decreases (increases) the weight of the most recent observations in the prediction. For instance, if it is chosen to be an infinitely large number, the resulting estimation will be identical to that of OLS. In another extreme, where the smoothing parameter is infinitely small, the coefficients will change dynamically over time, achieving a perfect fit. Here, d_j is just a scaling parameter and will make a material difference only if the variables are measured in different units or have disproportionate variances.

Since regression coefficients can be learned from the data in a recursive way, there is a connection between the FLS and Kalman filtering/smoothing (KF) methods. However, they operate on different principles as Kalman filtering assumes that errors are normally distributed and use maximum likelihood algorithm, whereas FLS makes no assumption on the distribution of errors and minimizes the cost function.[37] Darvas and Varga (2012) compared FLS to KF via a Monte Carlo study and reported FLS with a given smoothing parameter of 100 can reasonably well uncover more gradual changes in parameters.[38]

The FLS model with two lags and without scaling takes the following form:

$$y_t^{BED,\ m} = \beta_{0t} + \beta_{1t} * \ y_t^{INTUIT,\ m} + \beta_{2t} * \ y_{t-1}^{INTUIT,\ m} + \beta_{3t} * \ y_{t-2}^{INTUIT,\ m} + \epsilon_t$$

$$\beta_{0t} = \beta_{0t-1} + \varepsilon_{0t}$$

$$\beta_{1t} = \beta_{1t-1} + \varepsilon_{1t}$$

$$\beta_{2t} = \beta_{2t-1} + \varepsilon_{2t}$$

[36]For Canada, the model includes no lags. Although the results are inconclusive in the case of UK, the two-lag structure provides the best out-of-sample performance.

[37]He (2005) and Montana, Triantafyllopoulos, and Tsagaris (2009) provide nice applications on the use of the FLS method in financial settings.

[38]They also find OLS is the best estimation method when parameters are constant. In the presence of changing parameters, FLS outperforms KF, with an optimal search range of the smoothing parameter of between 34 and 355.

$$\beta_{3t} = \beta_{3t-1} + \varepsilon_{3t}$$

$$\underset{\epsilon_t, \varepsilon_{it} \in \mathbf{E_t}, \beta_{j,t} \in \mathbf{B_t}}{\operatorname{argmin}} R(\mathbf{E_t}(\mathbf{B_t})) = \sum_{t=1}^{T} \epsilon_t^2 + \lambda * \sum_{t=1}^{T} (\varepsilon_{0t}^2 + \varepsilon_{1t}^2 + \varepsilon_{2t}^2 + \varepsilon_{3t}^2)$$

$$\mathbf{B_t} = [\beta_{0t}\ \beta_{1t}\ \beta_{2t}\ \beta_{3t}]$$

We apply the FLS regression model to our data. Estimated coefficient values for the constant and lags (0, 1, and 2) take different but consistent values within their own past (see Figure 38 and 39).

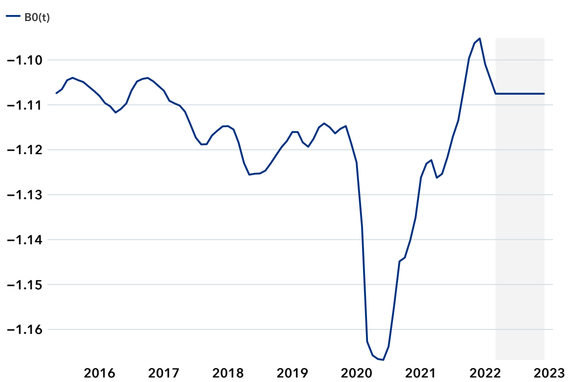


Figure 38: Time varying coefficients from FLS regression estimation, λ=100, 1-9 employment

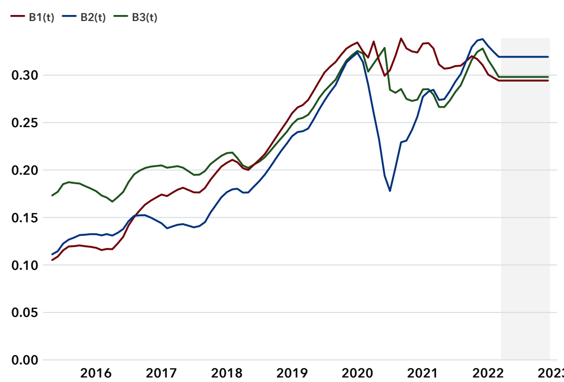


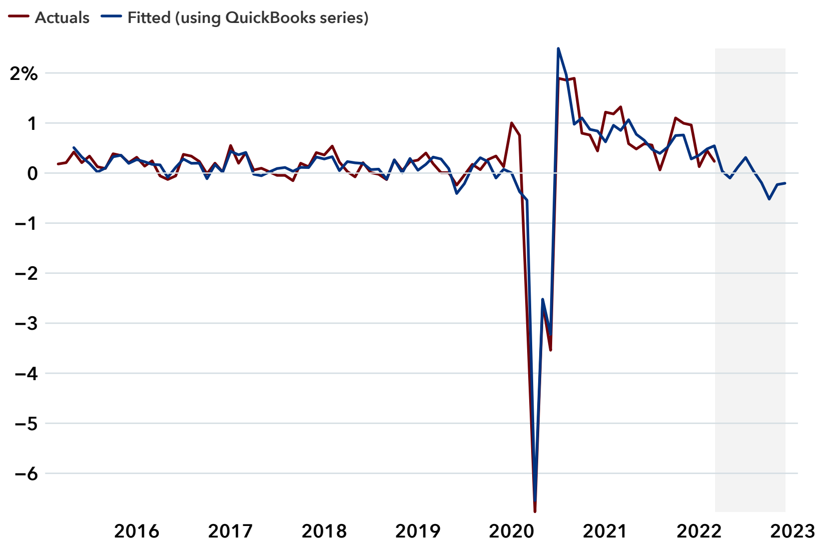
Figure 39: Time varying coefficients from FLS regression estimation, λ=100, 1-9 employment

The estimated coefficients provide us with sufficient flexibility to generate successful fits for both the monthly BJC and the quarterly BED series (see Figures 40 and 41). Note that the intercept term in Figure 38 acts as a shift parameter. It moves over, during and immediately after the COVID-19 shock. Interestingly, the coefficients of lags in Figure 39 increase in magnitude over time perhaps as a result of platform use. Finally, note the parameters cease to be updated after the last available BED observation. These parameters are then used for out of sample prediction. As a reminder, the monthly BJC series is constrained to match the BED at a quarterly frequency.

6.1.1 Parameter Tuning and Out-of-Sample Performance

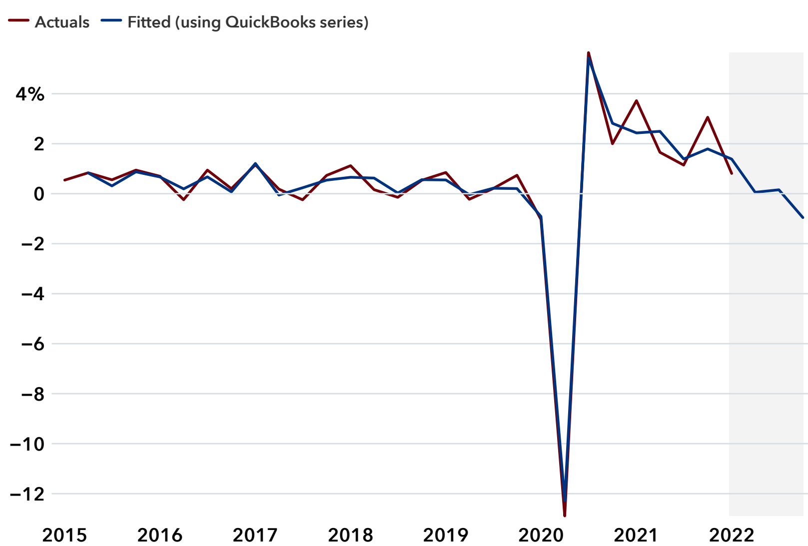
It is no surprise that FLS generates near-perfect fits. The FLS model will find adjustment factors for levels of the QuickBooks series such that the resulting index will match to those of BJC. The FLS method achieves that by estimating a different constant and slope coefficient at each point in time. We now turn to fine-tuning our model for out-of-sample performance. This involves identifying the optimal smoothing parameter "λ" that will minimize the Root Mean Square Error (RMSE) between the predicted and the actual series.

As mentioned earlier, at any given time, the latest available JOLTS and BED observations lag the QuickBooks series anywhere between one to two and six to eight months, respectively. For example, on the first day of October 2020, the QBO Payroll sample data for September 2020 is available, the BED data for the first quarter of 2020 and the JOLTS data for July/August 2020



Note: Shaded area indicates the months after the last available BED observation.

FIGURE 40: BED-JOLTS COMPOSITE (BJC), ACTUAL VS. FITTED FROM FLS REGRESSION ESTIMATION, λ=100, 1-9 SIZE CLASS



Note: Shaded area indicates the months after the last available BED observation.

FIGURE 41: BED QUARTERLY, ACTUAL VS. FITTED FROM FLS REGRESSION ESTIMATION, λ=100, 1-9 SIZE CLASS

are released (see Table 1). Our methodology allows us to generate monthly forecasts six to nine months out. Every three months however –with each new release of the quarterly BED, we can update our forecasting parameters.

To assess model performance and to fine tune the smoothing parameter, λ, we use the index itself as a potential explanatory variable for forecasting the BED series. As an example, we take the BED sample period of 2015q1-2018q4 and combine it with the monthly JOLTS data to create our BJC monthly series.[39] We then estimate the relationship between the QBO Payroll

[39] Note that changing the sample period will result in different monthly BJC series.

Month	Year	BED (train)	JOLTS (train)	BJC (train)	Intuit (train)	BED (test)	Intuit (test)	JOLTS (test, not used)
January	2015		0.5	0.3	4.9			
February	2015		0.1	0.1	0.9			
March	2015	0.6	0.3	0.2	5.0			
April	2015		-0.3	0.2	4.9			
May	2015		0.3	0.5	4.7			
June	2015	0.9	-0.3	0.2	2.9			
...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...
October	2019		0.3	0.4	2.3			
November	2019		0.5	0.5	1.0			
December	2019	1.2	0.0	0.3	2.4			
January	2020						**1.5**	**0.7**
February	2020						**-1.1**	**0.0**
March	2020					**-1.2**	**1.3**	**-10.1**
April	2020						**-15.1**	**-6.6**
May	2020						**9.4**	**5.2**
June	2020						**6.9**	**2.5**
July	2020						**2.2**	**1.3**
August	2020						**3.4**	
September	2020						**4.2**	

Table 1: Train and Test/Forecast availability of data sets as of first week of October 2020.

sample data and the BJC data using the FLS model outlined in Section 6.1. Finally, we use the estimated parameter values to extend the forecast horizon depending on the length of available QBO Payroll sample data, which is at least six months as per the following model:

$$y_{t+h}^{BED,\,m} = \beta_{0t+h} + \beta_{1t+h} * \ y_{t+h}^{INTUIT,\,m} + \beta_{2t+h} * \ y_{t-1+h}^{INTUIT,\,m} + \beta_{3t+h} * \ y_{t-2+h}^{INTUIT,\,m}$$

where $\beta_{0t+h} = \beta_{0t}$, $\beta_{1t+h} = \beta_{1t}$, $\beta_{2t+h} = \beta_{2t}$, and $\beta_{3t+h} = \beta_{3t}$, thus keeping the forecasting parameters fixed at the estimated values as of 2018q4 (or December, 2018) (see Figure 38). We update the model with each newly available quarterly BED.

To optimize λ we grid-search with large steps and compute the RMSE between the actual and the predicted series. We do this both for the BJC series as well as the quarterly BED series. Note, interpolation, seasonal adjustment and forecasting occur at the monthly level, but for comparison to the quarterly BED we aggregate the net growth values as appropriate (see Figure 43 and Figure 45). We find that lambda value of 100 outperforms other choices. Table 2 summarizes the RMSE for these values. Two things are relevant of note at this point. First, although the forecasting parameters were estimated before the COVID-19 shock, they are still able to predict the decline, recovery, and slow adjustment back over the 2021 and 2022 periods. This gives us confidence that the relationship between the QuickBooks and the BED net flow series is captured by the FLS model is fairly robust across the COVID-19 shock and by extension likely across business cycle shocks. Second, our λ parameter is optimized for the entire period covered by the COVID shock and the recovery. This extends to a period when we use parameters estimated at the height of the COVID shock to predict our series nine months later. By doing so, we minimize human intervention. Use of different λ values during (or before and after) such turbulent periods will be considered in the future once enough data is available for this exercise.

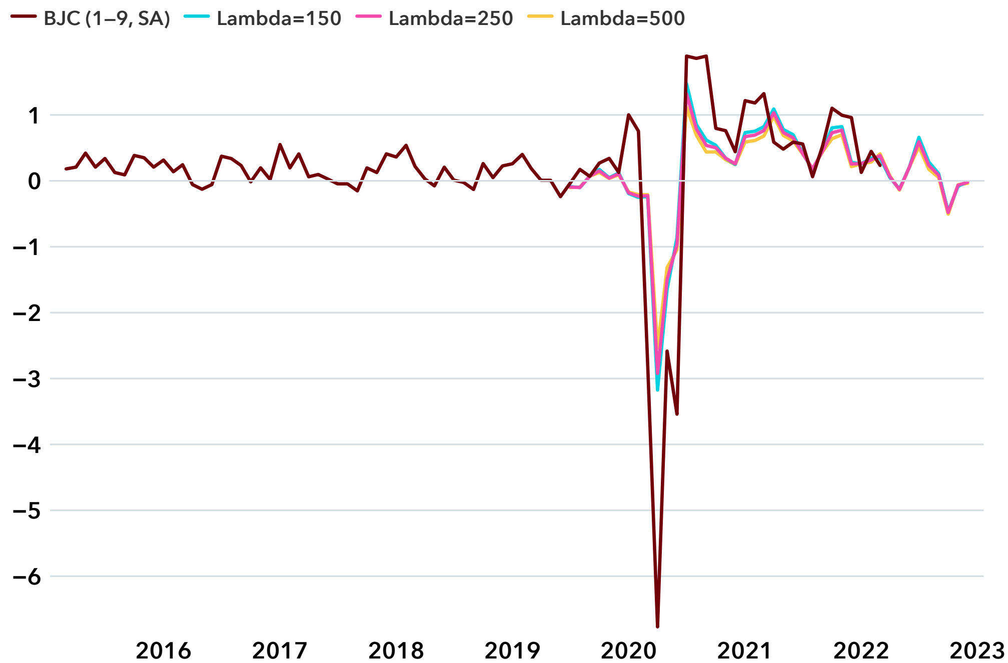


Figure 42: Out-of-sample forecasts for 7 to 9-months, updated every 3-months, SA, 1–9 size class, monthly frequency.

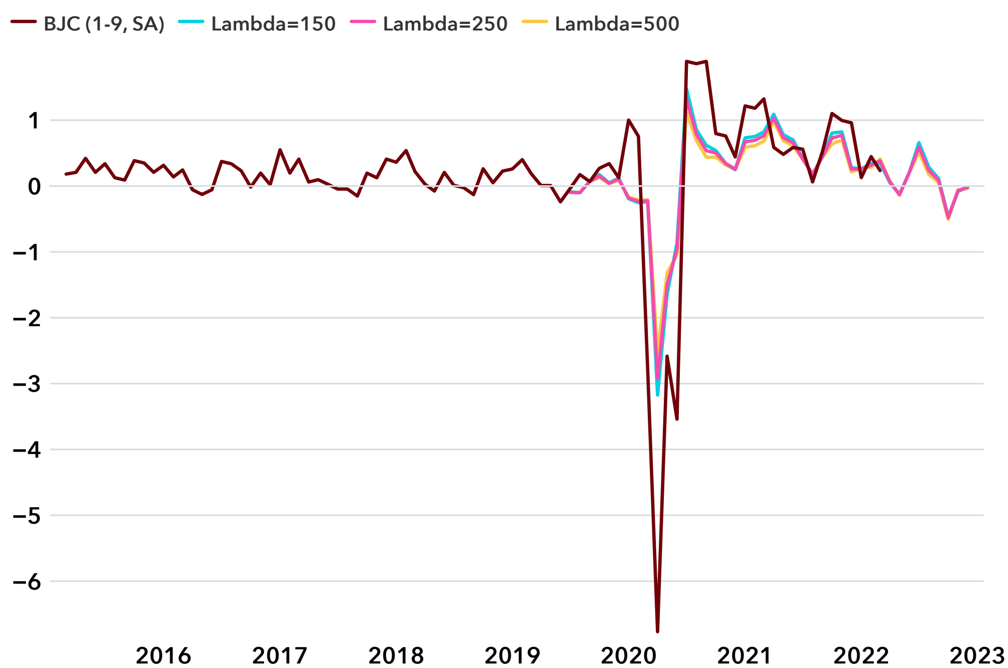


Figure 43: Out-of-sample forecasts for 7 to 9-months, updated every 3-months, SA, 1–9 size class, monthly frequency.

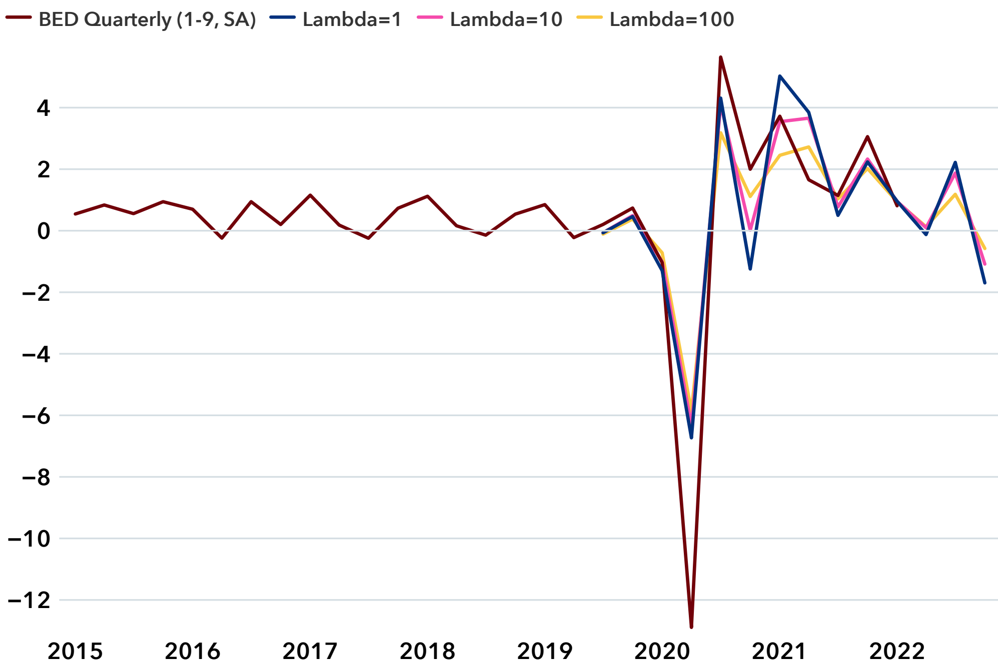


Figure 44: Out-of-sample forecasts for 7 to 9-months, updated every 3-months, SA, 1–9 size class, quarterly frequency

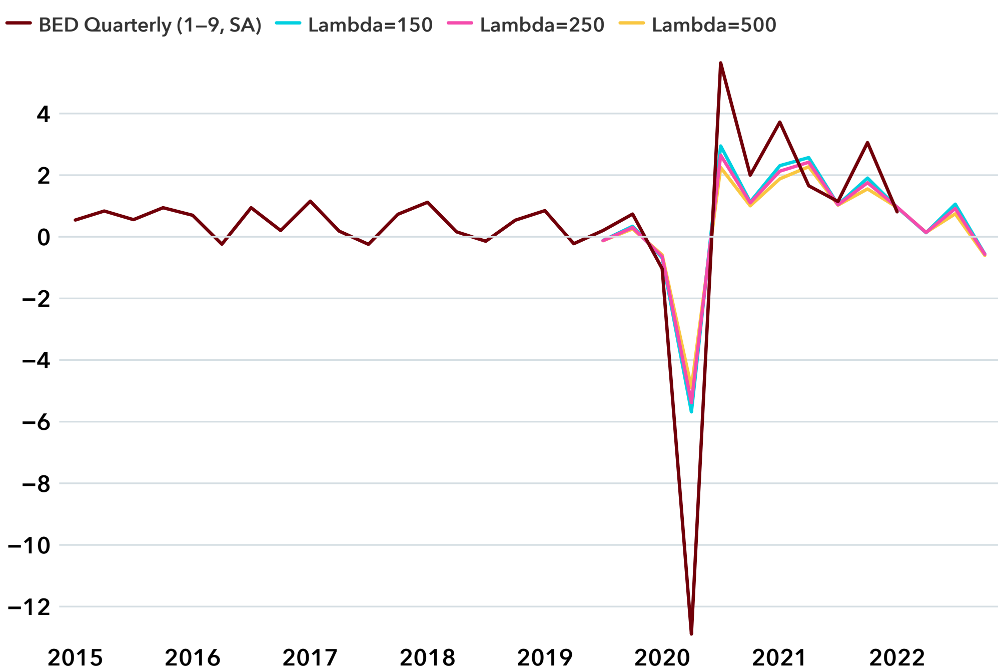


Figure 45: Out-of-sample forecasts for 7 to 9-months, updated every 3-months, SA, 1–9 size class, quarterly frequency

λ	1	10	100	150	250	500
RMSE	1.19	1.08	1.01	1.03	1.06	1.12

Table 2: Root Mean Square Error: BJC Series minus Forecast.

6.1.2 Other Considerations

Having settled on our basic methodology for the national series, we now consider a number of extensions. First, we assess the performance of an index that relies on more limited information but is more timely in return. Second, we consider a series that considers only continuer firms and thus excludes entry and exit. Third, we extend the method to the geography and industry series.

We strive to produce and release the Index as early as possible each month while retaining accuracy. At the moment, it takes five days to collect data, process it and generate our index. To understand the trade-off between timeliness and accuracy, we move the cut-off date back five days and repeat the analysis in Section 6.1.1. In other words, we use 25 days worth of data rather than the full month. We then assess how the loss of information affects the overall quality of the index.

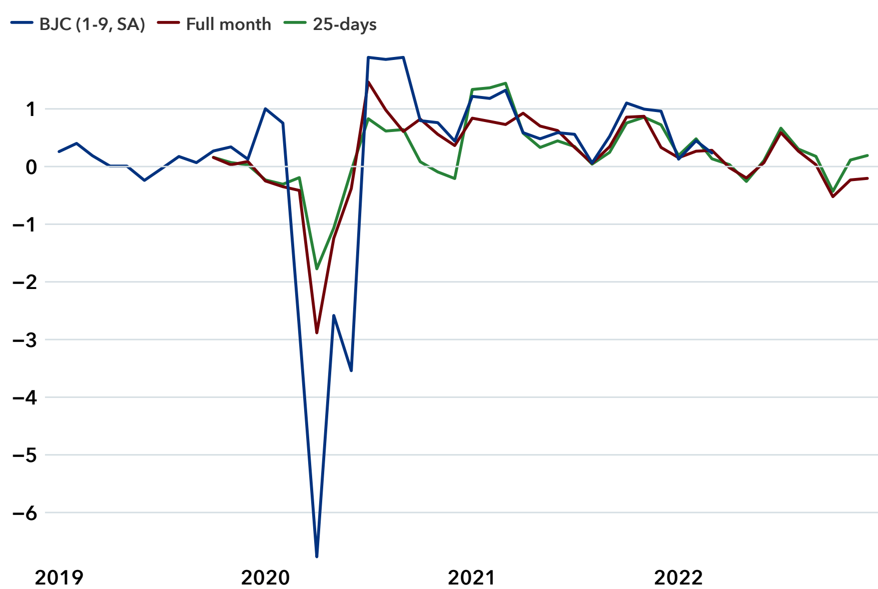


Figure 46: Comparison of out-of-sample forecasts from full month and 25-days, 1–9 size class.

Figure 46 compares out of sample results for the 25-day index versus the full-month index. The RMSE relative to the BJC is 1.35 versus 1.15 basis points respectively, and the correlation coefficient between the two series is 0.86. Differences in the prediction during, and in the two months immediately after, the COVID-19 shock drove most of the difference between the two series. Differences between the two series are minimal after that. The implication is that during periods of large reallocation the 25-day index doesn't perform quite as well as the full information index. It would be ideal to monitor the difference between the two series and provide an updated set of projections based on the 30-day index if necessary.

The FLS methodology is designed to calibrate the raw QBO Payroll sample data to the official statistics in a dynamic way. It is powerful in the sense that it can accommodate large discrepan-

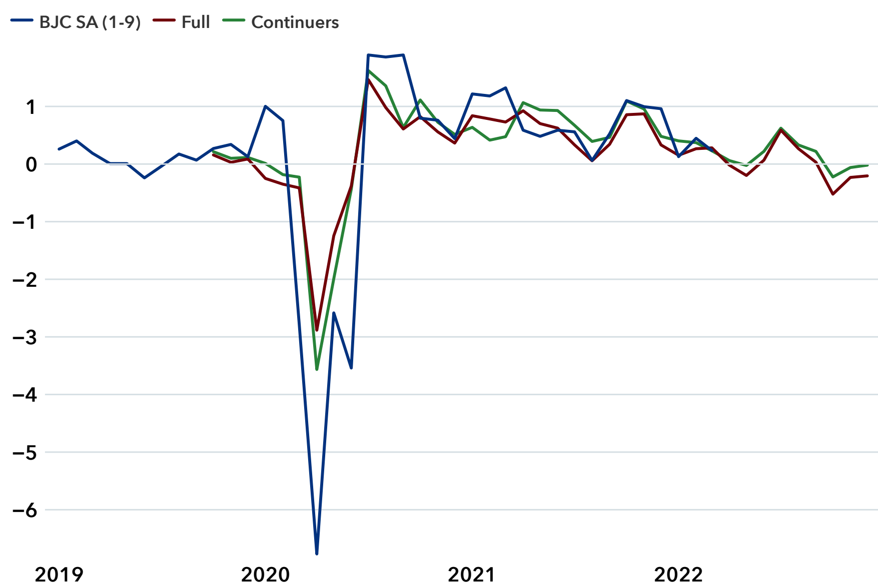


Figure 47: Comparison of out-of-sample forecasts from full and continuers, 1–9 size class

cies between the two series — for example, as a result of the entry and exit dynamics into the QuickBooks Online Payroll platform. However, there is potential value in distinguishing between the full series — incorporating all margins of adjustment, and one that includes only continuer firms. In this exercise we target the same monthly BJC series but now using only Intuit firms that are present both in the current and previous month. Figure 47 provides the results from this exercise. The two series do not differ in a qualitatively significant manner.

The COVID-19 shock made it abundantly clear disruptions to economic activity can have very different impacts on the different productive sectors and geographic areas. Our goal is to provide timely and valuable information at the national level first, but also by industry and geography. As we consider extending our methodology to accommodate this type of heterogeneity, we need to consider again what is available in the official statistics. JOLTS and BED provide information about industry or geography, but not on the interaction. Furthermore, this information is only available for all firms regardless of size. There is no specific information for small firms. We could generate a target BJC series based on this information. We would then target industry/geography specific series for the economy as a whole to estimate a new series of FLS parameters. In doing so we would lose the information that pertains to small businesses. Alternatively, we can use the parameters already estimated from the national model and use the industry/geography specific QuickBooks series to create our small business out-of-sample forecasts. Inherently, we are assuming that the parameters governing the relationship between the QBO Payroll sample data and the actual data do not fundamentally change across industries and geographies. In this sense, the underlying entry, exit, and growth dynamics of the different sectors and geographies drive all of the variation between the national and the industry/geography series. We explore the results of this exercise in the following section.

7 Intuit QuickBooks Small Business Index

In this section we provide our first look at the Intuit QuickBooks Small Business Index. We generate an out-of-sample series beginning in 2022q2, the most recent release of the Bureau of Labor Statistics BED data. We compare the 25-day index and the full-month index. We also describe the series for selected geographies and industries. Finally, we review the Intuit QuickBooks Small Business Index for the UK and Canada and discuss some limitations of those series and potential improvements moving forward.

7.1 Intuit QuickBooks Small Business Index: US

Figure 48 shows the Intuit QuickBooks Small Business Index for the US. The shaded area displays out-of-sample projections. The 25-day index and the full information index are displayed against the BJC. The full-month index displays a sharper decline in the Fall of 2022 and a sharper recovery late in the year and early 2023. Figures 49 and 50 display net job creation patterns by industry. Our index displays considerable variation across broad sectors. As expected the Accommodation and Food sectors experience the biggest declines followed by Arts and Entertainment, and Wholesale during COVID. These sectors also experienced the largest recoveries. The least affected sectors were Professional Services and Finance, followed by Construction and Manufacturing. In late 2022 we see declines across the board with the smaller declines in Agriculture and Mining, and Utilities, followed by Education, and Professional Services. The largest declines were in Information, Transportation, and Leisure.

Figure 51 shows results by Bureau of Economic Analysis (BEA) region. Small business activity experienced sharper declines in the Midwest, New England, and the Great Lakes regions during COVID. Least affected were the South, and the Rocky Mountain area. All areas appear to be negatively impacted in late 2022 with the New England region experiencing the smallest declines.

7.2 Intuit QuickBooks Small Business Index: UK and Canada

Fig. 52 and 53 plot the QuickBooks Index for Canada and UK using the methodology described in the Section 6. An important difference here is that our benchmark statistics are highly current, so we need only project one period ahead before we have new data points with which to update the model parameters. The lag structure is the same as in Section 6 for UK but for Canada we only use the contemporaneous values with $\lambda = 100$ in both the series.

8 Conclusions

Small businesses are engines of employment and economic growth. Despite the vital roles they play in every economy, it is hard to construct a timely measure of their business health due to lack of systematic real-time data. The Intuit QuickBooks Small Business Index is a major attempt

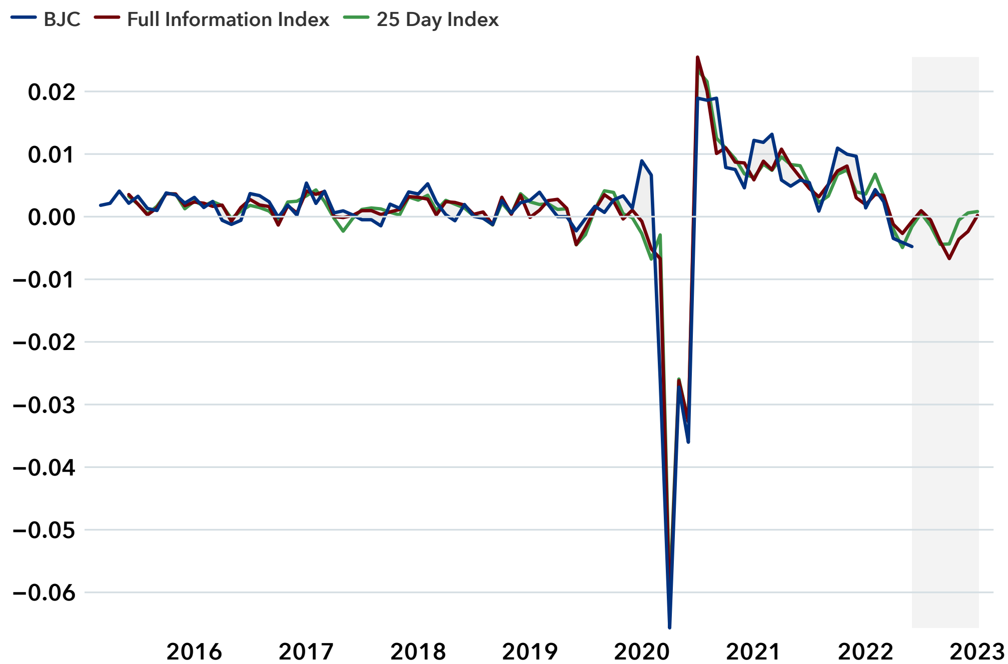


FIGURE 48: US NATION 25 DAYS VS. 30 DAYS: IN-SAMPLE THROUGH 2022Q2 OUT OF SAMPLE AFTER. GRAYED AREA AFTER 2022Q2.

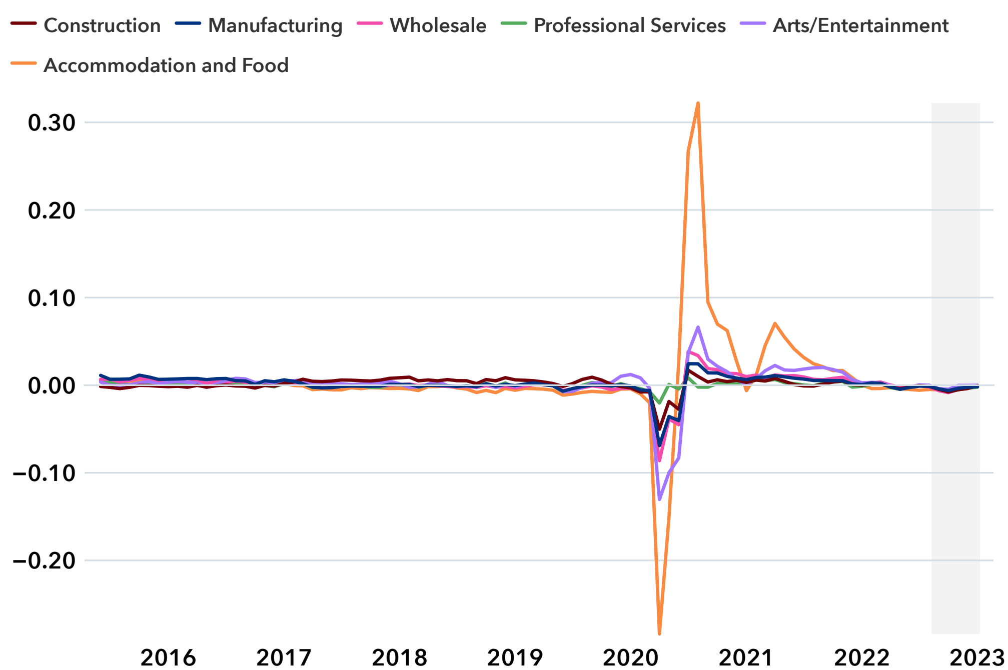


FIGURE 49: US SELECTED INDUSTRIES: IN-SAMPLE THROUGH 2022Q2 OUT OF SAMPLE AFTER. GRAYED AREA AFTER 2022Q2

to fill this important gap. The QuickBooks Index is a new monthly indicator of employment and hiring among the smallest of small businesses in the US, Canada, and the UK. Further, the Index benefits from the unique position and broad user base the Intuit platform enjoys among small businesses. This paper describes the steps taken to build the index.

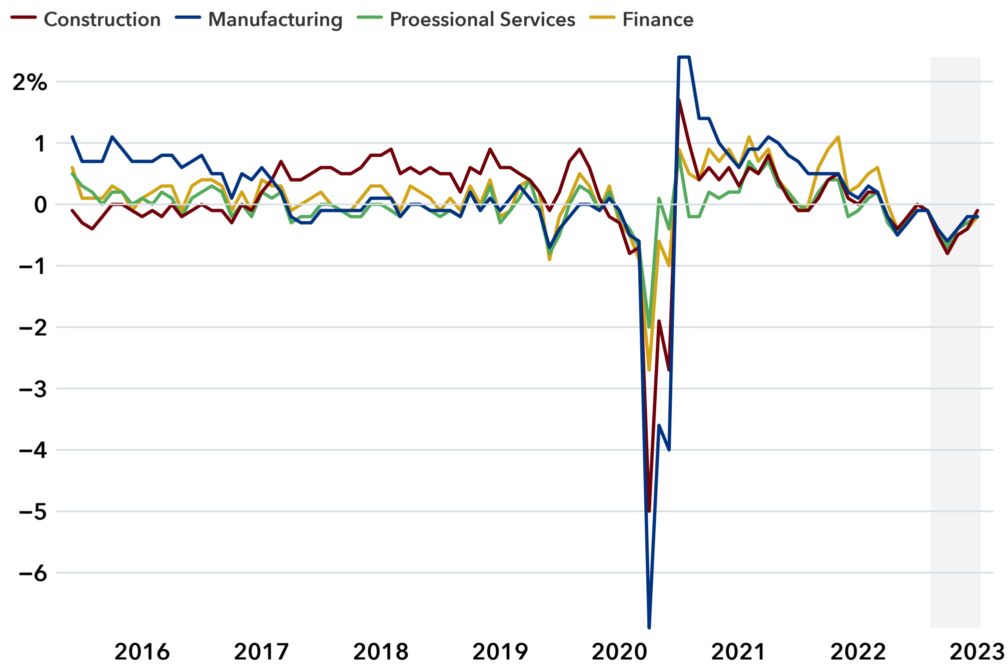


FIGURE 50: US SELECTED INDUSTRIES: IN-SAMPLE THROUGH 2022Q2 OUT OF SAMPLE AFTER. GRAYED AREA AFTER 2022Q2

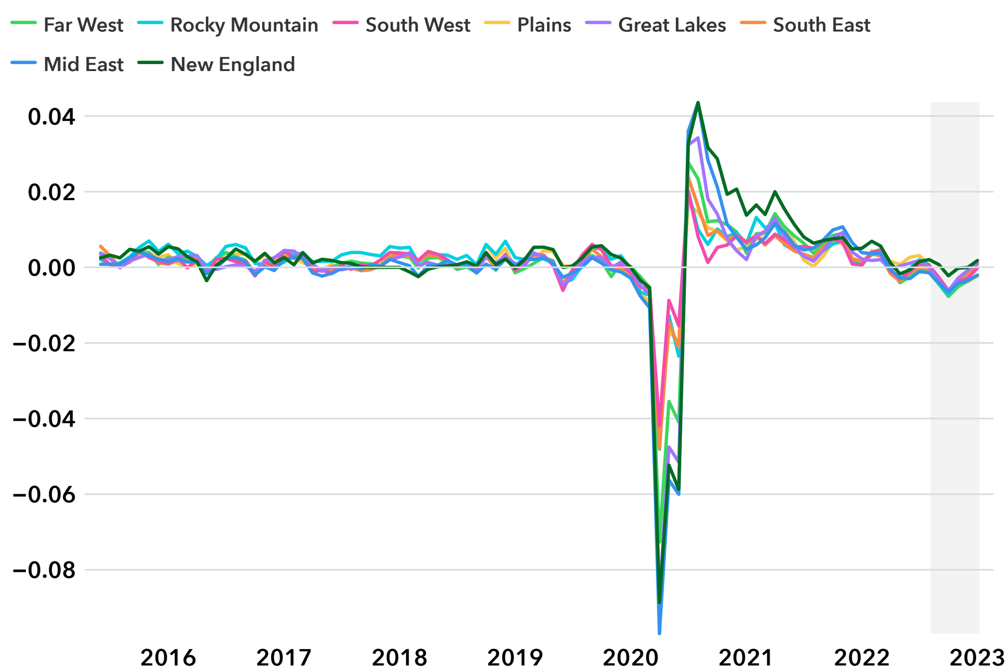


FIGURE 51: US SELECTED BEA REGIONS: IN-SAMPLE THROUGH 2022Q2 OUT OF SAMPLE AFTER. GRAYED AREA AFTER 2022Q2

First, we compare QBO Payroll sample data to official statistics in the three countries. Second, we remove seasonal components and use a Flexible Least Squares method to bridge the gap between the official statistics and the QBO Payroll sample data. Third, we use the coefficients of the estimated model to produce our near real time index, a set of (out-of-sample) projections

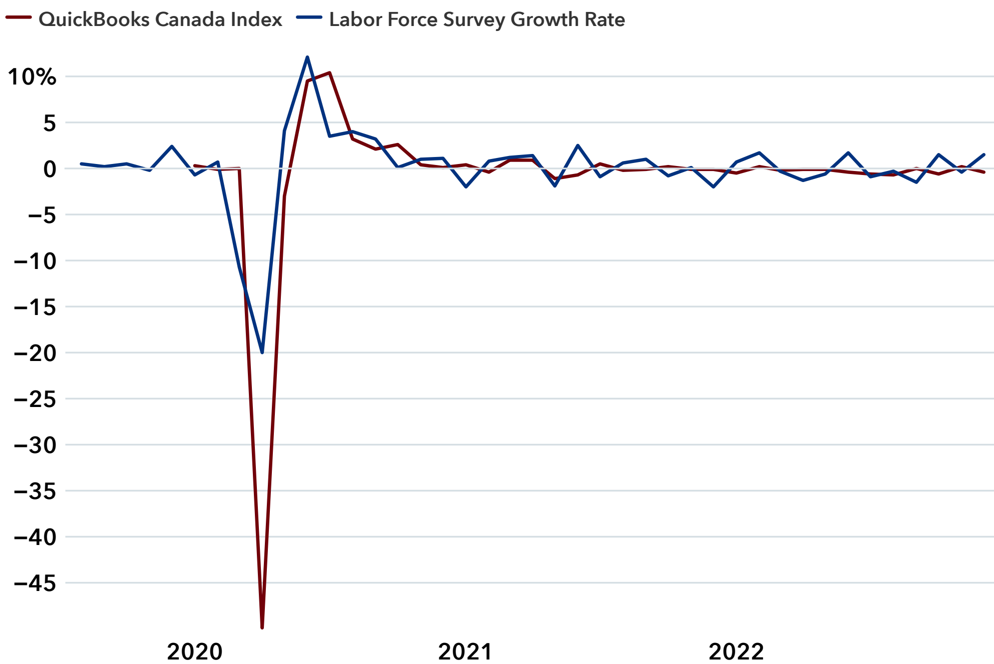


FIGURE 52: CANADA QUICKBOOKS INDEX WITH $\lambda = 100$

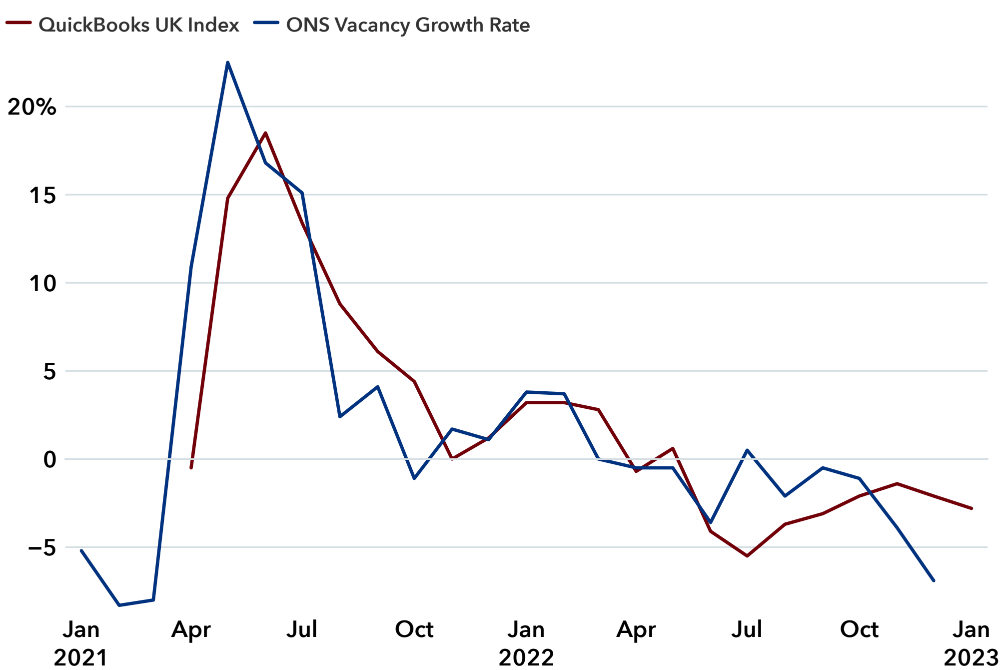


FIGURE 53: UK QUICKBOOKS INDEX WITH $\lambda = 100$

based on Intuit's transaction data. We show that the estimated model performs very well both in-sample and out-of-sample. We then generalize this analysis to different regions and industries.

The methodology we developed is robust, allowing us to target a range of official statistics in the US, Canada, and the UK. The value of the Index in the US is more obvious in that we are able to provide indicators of small business activity months in advance of any official estimate. For the US, the Intuit QuickBooks Small Business Index targets benchmark official statistics derived from administrative data including the full population of small businesses. These data represent the gold standard when it comes to describing small business activity. In this regard, the QuickBooks Index is particularly valuable.

In the UK and Canada we target current survey data instead. Survey data is subject to unknown bias as well as sampling errors in ways that we do not fully understand. Our preference is to target benchmark official estimates from the population of small businesses from administrative records. However, these are not currently available – they are either not produced or have not been recently updated. The QuickBooks Index for these countries will be released only two weeks before the release of official survey-based estimates. We hope to engage with statistical offices in Canada and the UK to assess the feasibility of targeting administrative data in the future. For the US we hope to engage with the BLS to assess the feasibility of incorporating monthly measures from the JOLTS series that address the drift between the JOLTS and the QCEW.

This paper describes only the first steps in the development of the QuickBooks Index. Our future work will incorporate new variables such as worker wages, business revenues, and inventory, among others, which open up the opportunity of providing unique insights about the population of small businesses and their employees. For the US we also plan to release additional estimates of job creation and job destruction, as well as Intuit's raw seasonally adjusted growth measures. Finally, our goal is to add countries to our list, data permitting.

The QuickBooks Index can provide insights about the small business economy in near real-time. In this sense, the QuickBooks Index provides an additional tool when making policy recommendations that directly impact small businesses. We hope that this index will be useful to policymakers and researchers alike.

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Appendix

A Canada and UK Official Statistics Data

A.1 Office of National Statistics (ONS) Vacancy Data

The UK ONS does not currently update its Business dynamism measures derived from the Inter-Departmental Business Register. This is a quarterly series of job creation, destruction, reallocation, and net growth by firm size. The series was discontinued in the last quarter of 2019. In its stead, we use the vacancy series, which provides an estimate of the number of jobs and vacancies in the U.K..[40]

We use the vacancy headline estimate for enterprises with between 1 and 9 employees, which is based on a seasonally adjusted, three-month moving average and has National Statistics status. The data come from a rotating survey of businesses rather than the whole population. Approximately 80% of the survey overlaps every three months, therefore a comparison of vacancy estimates for a given month to three months prior can provide a reasonable indication of the change in monthly vacancies.

Vacancies — as in the JOLTS data, are defined as positions for which employers are actively looking to fill from outside their business or organization. Estimates cover the whole economy, excluding agriculture, forestry, and fishing (sample size makes it impractical to provide estimates for these small sectors).

Vacancies data are available by sector but not by size at this time. In as much as we target this series in our UK Small Business indicator, the QuickBooks series will reflect broader activity than just that for small businesses. We use these data for the calibration exercise.

The vacancy data are released 15 days after the end of the reference month. In this sense, the data are extremely current, thus limiting the value of our Intuit series which comes only 15 days earlier. Use of vacancy data for calibration is not ideal for our purpose. It limits the types of information we can generate from the QuickBooks user data itself. We consider this a first approach to further refinements that we expect will yield more valuable data series in the future.

A.2 Statistics Canada Business Dynamics Measures

Statistics Canada produces an annual series of business dynamism measures including net growth and job creation and destruction by firm size from their Longitudinal Employment analysis Program (LEAP). The program draws from administrative records; specifically, the annual statements of remuneration paid (T4 slips) that Canadian businesses are required to provide their

[40]The Business Dynamism measures can be found at, https://www.ons.gov.uk/businessindustryandtrade//changestobusiness/businessbirthsdeathsandsurvivalrates/datasets//businessdynamismmeasuresfromtheinterdepartmentalbusinessregisteruk. The vacancy series can be found at https://www.ons.gov.uk/employmentandlabourmarket//peopleinwork/employmentandemployeetypes/bulletins/jobsandvacanciesintheuk/october2022

employees for tax purposes. The target population of LEAP is every employer in Canada regardless of incorporation. The series starts in 2016 and currently runs to 2020. The low frequency data and severe lag require we turn in its stead and for the time being to the monthly series of employment by establishment size from their Labor Force Survey (table 14-10-0067-01).[41] We use these data for the calibration exercise. Our use of these data limits what we can generate from the data. We consider this a first approach to further refinements that we expect will yield more valuable data series in the future.

The LFS uses a probability sample that is based on a stratified multi-stage design that starts with the province and clusters within the provinces. The target population is the population 15 years of age and over. The survey is conducted nationwide and excludes persons living on reserves, Aboriginal settlements, full-time members of the Armed Forces, the institutionalized population, and households in extremely remote areas. These groups together represent an exclusion of less than 2% of the Canadian population aged 15 and over. The LFS sample size is approximately 56,000 households, corresponding to approximately 100,000 individuals. This can change to meet data quality or budget requirements. Since the LFS is a sample survey, all estimates are subject to both sampling and non-sampling errors. Nonresponse rates average about 10% of eligible households. We obtain seasonally adjusted data. The method used for seasonal adjustment is X-12-ARIMA.

The Labor Force Survey (LFS) provides estimates of employment and unemployment as well as important labor market indicators such as the employment rate and the participation rate. The survey limits the amount of detail that is available by type of business. Starting in January 1997, the number of employees at the physical location of employment (establishment or plant) is collected from employees. Responses are recorded according to the following size categories: establishments with less than 20 employees, 20 to 99 employees, 100 to 500 employees, and more than 500 employees. Tabulations by 2-digit NAICS sector –including public administration, and province are available. Territories are excluded. The reference period is the week containing the 15th day of the month. We make use of the private sector tabulations for the smallest size class available, by industry and province when available. Certain data cells are suppressed to comply with the confidentiality requirements of the Statistics Act. This affects the Utility series by province in particular. We find no other suppressions at this level of disaggregation.

The LFS data are released 10 days after the close of the reference month. In this sense, the data are extremely current, thus limiting the value of the QuickBooks series, which comes only 10 days earlier. The use of LFS data for calibration is not ideal for our purpose. It limits the types of information we can generate from the data itself. We consider this a first approach to further refinements that we expect will yield more valuable data series in the future.

[41]We will explore using these data for the creation of a timely job creation and destruction series from QuickBooks Canada.

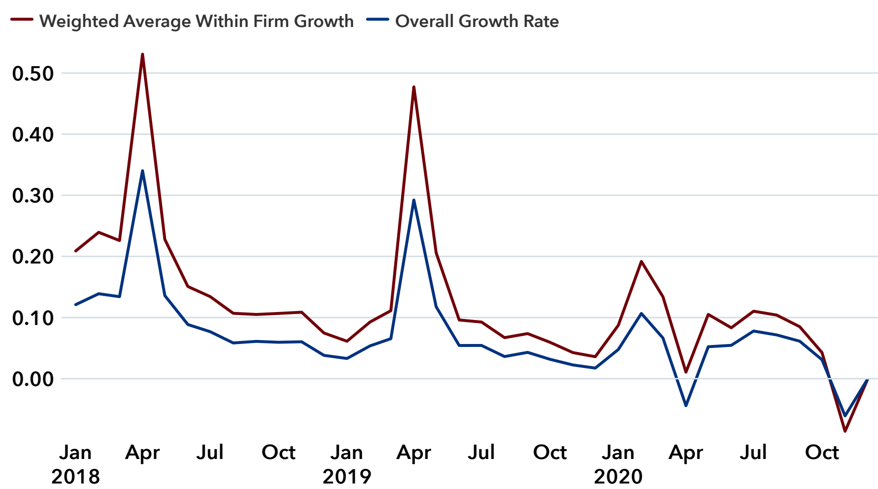
B Margin Definitions

Margin	Set	Firm i is in this set if	Definition
Expansion	$\mathcal{A}$	active subscriber in both period t and $t-1$ $0 < E_{i,t-1} < E_{i,t}$	$\sum_{i \in \mathcal{A}}(E_{i,t} - E_{i,t-1})$
Contraction	$\mathcal{B}$	active subscriber in both period t and $t-1$ $0 < E_{i,t} < E_{i,t-1}$	$\sum_{i \in \mathcal{B}}(E_{i,t} - E_{i,t-1})$
Opening	$\mathcal{C}$	either active subscriber in both period t and $t-1$ $E_{i,t-1} = 0$ and $E_{i,t} > 0$ $E_{t-1} = 0$ if they had payroll but didn't pay anyone or did not have payroll at all	$\sum_{i \in \mathcal{C}}(E_{i,t} - E_{i,t-1})$ +
	$\mathcal{D}$	or Birth: active subscriber in t and was not on QuickBooks in $t-1$ $E_{i,t-1}$ automatically zero $E_{i,t} > 0$	$\sum_{i \in \mathcal{D}}(E_{i,t} - E_{i,t-1})$
Closing	$\mathcal{E}$	either active subscriber in both period t and $t-1$ $E_t = 0$ and $E_{i,t-1} > 0$ $E_t = 0$ if they have payroll but didn't pay anyone or stop using payroll at all	$\sum_{i \in \mathcal{E}}(E_{i,t} - E_{i,t-1})$ +
	$\mathcal{F}$	or Death: active subscriber in $t-1$ and leaves QuickBooks in t $E_{i,t}$ automatically zero $E_{i,t-1} > 0$	$\sum_{i \in \mathcal{F}}(E_{i,t} - E_{i,t-1})$

TABLE 3: $E_{i,t}$ DENOTES TOTAL EMPLOYMENT IN PERIOD t IN FIRM i

C Growth Dynamics: QuickBooks UK and Canada

C.1 Intuit QuickBooks UK Employment Data

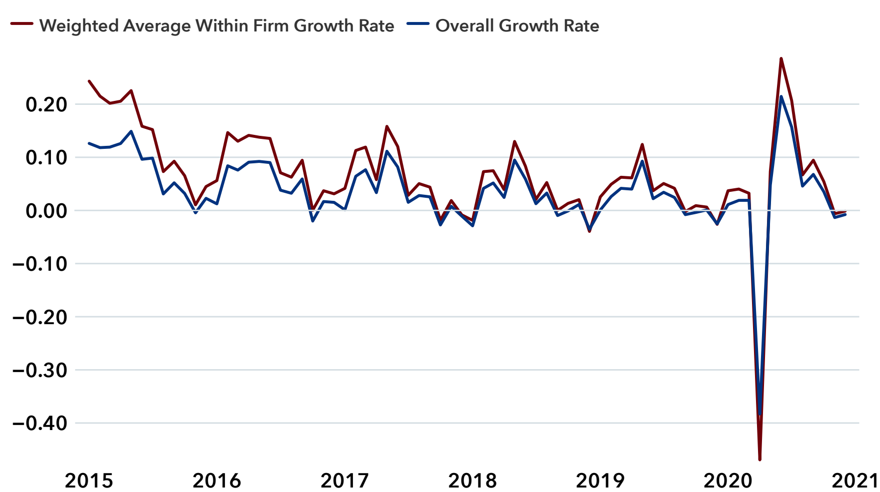


Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.

Source: QuickBooks Online Payroll Sample UK

Figure 54: Growth Rates for UK

C.2 Intuit QuickBooks Canada Employment Data



Note: Data points post-December 2021 are used, but not shown in the figure to comply with confidentiality requirements.

Source: QuickBooks Online Payroll Sample Canada.

Figure 55: Growth Rates for Canada

D Seasonal Adjustment

As discussed in Section 5.3, the overall growth rate masks different seasonality in the underlying components. Fig 56, 57, 58 and 59 show the raw and seasonally adjusted expansions, contractions, openings and closings. Note that the figures omit data points post-December 2021 to comply with confidentiality requirements.

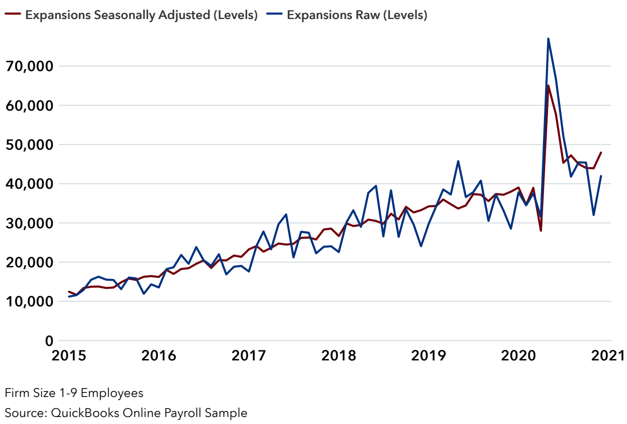


Figure 56: Seasonality in Expansions. Size 1–9

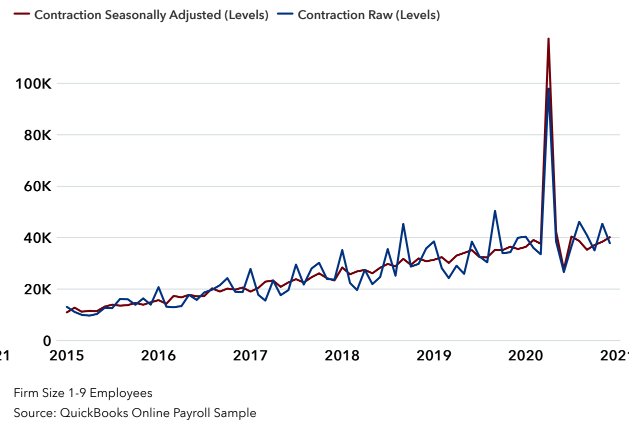


Figure 57: Seasonality in Contractions. Size 1–9

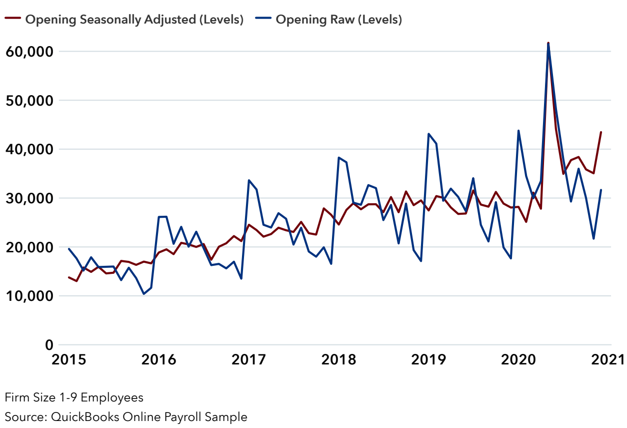


Figure 58: Seasonality in Openings. Size 1–9

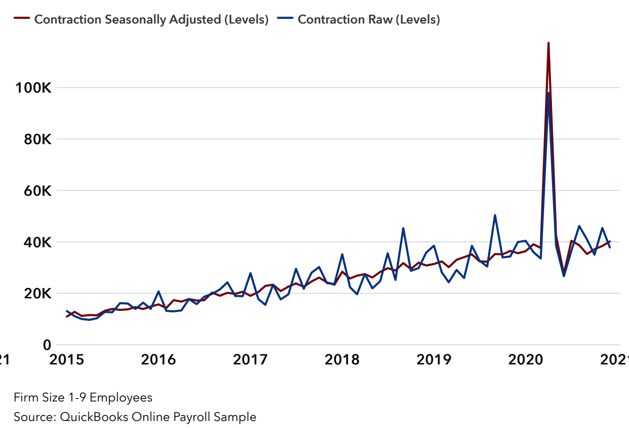


Figure 59: Seasonality in Closings. Size 1–9

E LASSO estimation

We implicitly assume that the relationship between Intuit and the official benchmark series is contemporaneous. Since we do not dispute that these data sets are conceptually different to begin with, there is no reason to refrain from looking for lagged effects.[42] We prefer to be agnostic and include the past effects up to 12 months.

The length of our sample is such that it does not allow us to include many potential explanatory variables. Furthermore, we suspect that the parameters may be regime-dependent due to changing circumstances over time. We use Machine Learning techniques to reduce the number of parameters in the model (Friedman et. al, 2001). Specifically, we use a LASSO regression. Our regularization allows estimated coefficients to shrink to zero depending on the value of the penalty parameter, λ:

$$\underset{\beta_j \in \mathbf{B}}{\operatorname{argmin}} R(\mathbf{B}) = \frac{1}{2T} \sum_{t=1}^{T} \left(y_t^{BED,\ m} - \beta_0 - \sum_{j=0}^{12} y_{t-j}^{INTUIT,\ m} \beta_{1j} \right)^2 + \lambda \sum_{j=0}^{12} |\beta_{1j}|$$

Since the choice of penalty parameter is of crucial importance, we resort to cross-validation techniques (another ML approach) to find the appropriate value. We are working on a time series data set, where we suspect that the estimated coefficients are not fixed over time; therefore we choose a “rolling window” approach. After a window size is chosen (36 months in our case), it is divided into training and test sets. [43] The window then “rolls” through the data set until it reaches the end of the sample (see Fig.60,61,62).

[42]We designed our regression approach to minimize the impact of sample composition effects, platform growth, and timing differences between the QuickBooks and the official data sets.

[43]Test sizes are 3, 1 and 2 months, following the 6, 1 and 1 announcement lags respectively, for US, Canada and UK.

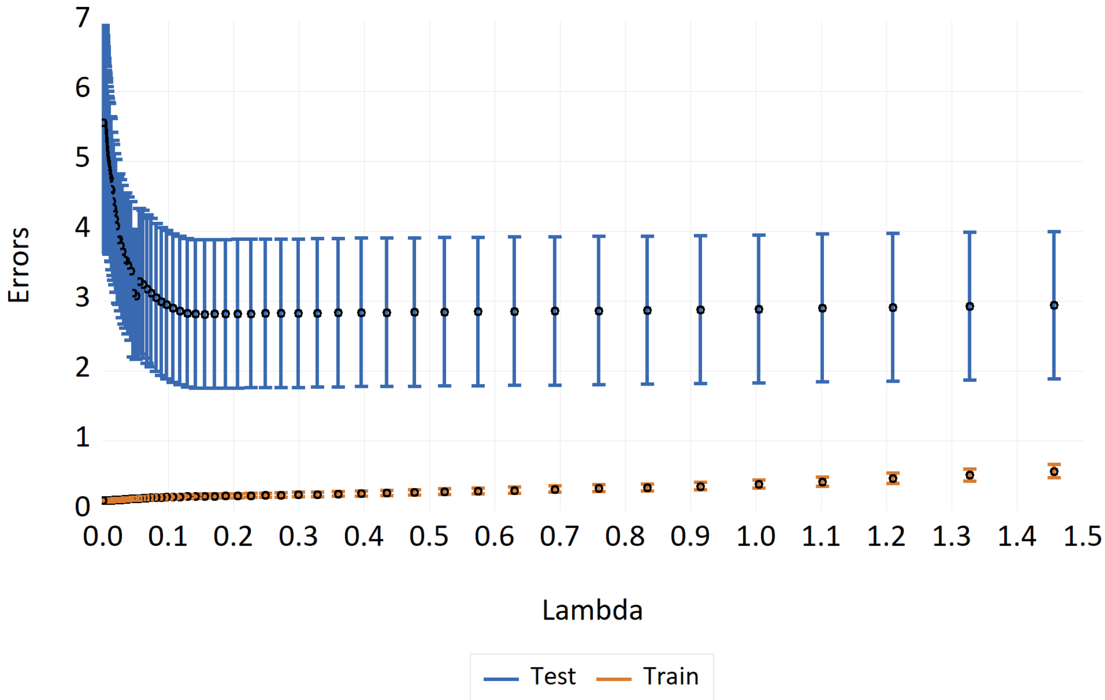


FIGURE 60: TRAIN/TEST ERROR EVOLUTION FROM LASSO REGRESSION ESTIMATION, US, 1–9 SIZE CLASS

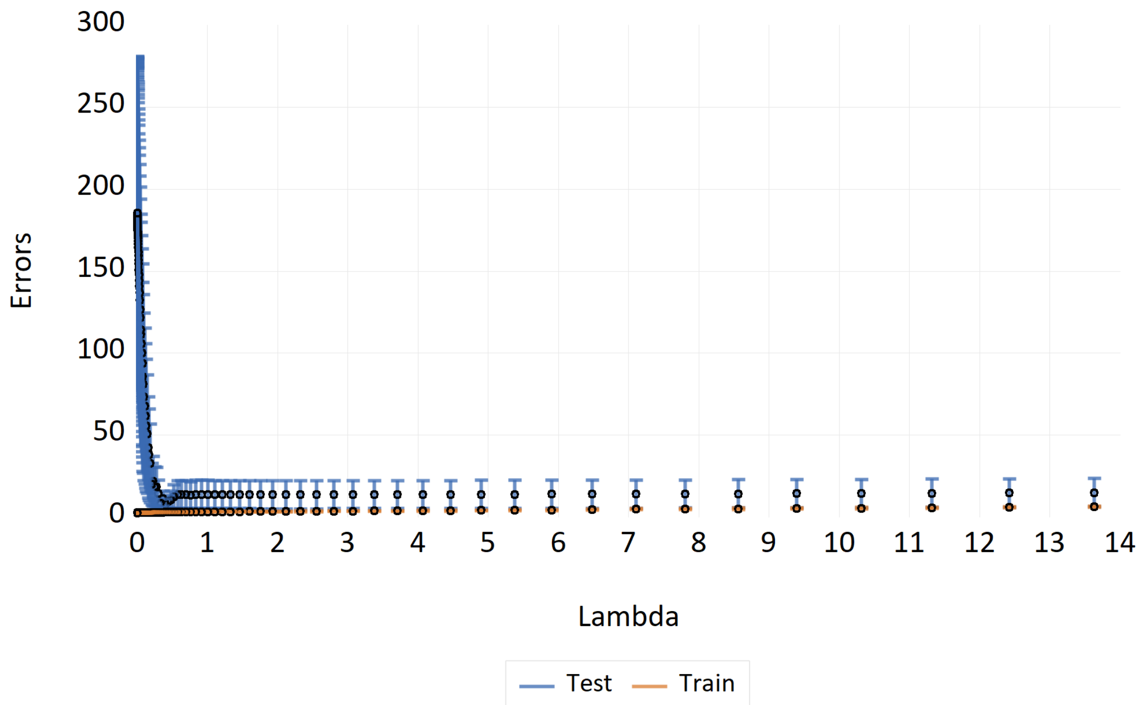


Figure 61: Train/Test error evolution from LASSO regression estimation, CAN, 1–19 size class

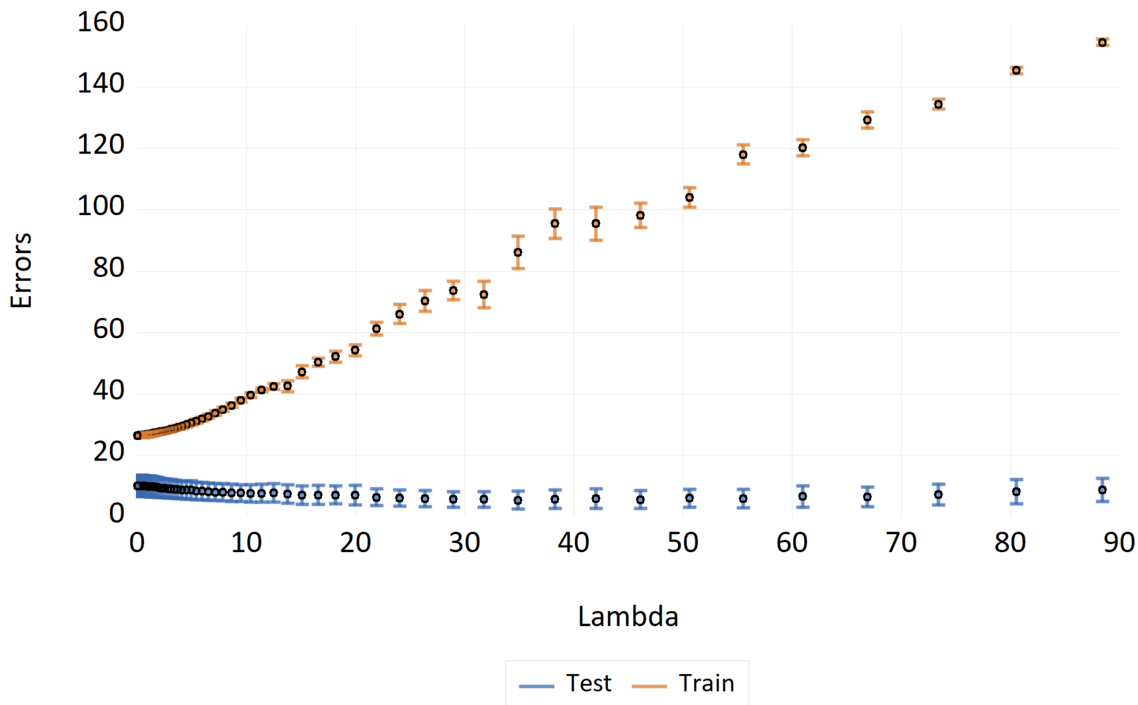


Figure 62: Train/Test error evolution from LASSO regression estimation, UK, 1–9 size class

Rolling window cross validation finds the optimal value of lambda parameter at 0.16 for the US case. As the value of the regularization penalty lambda increases, the absolute value of each of the coefficients decreases and may end up zero (see Fig.63,64,65). This is the expected result for this type of penalized regression. The thin black vertical line is the minimum value of lambda selected by cross-validation.

The analysis reveals that first and second lags of QBO Payroll sample data also carry useful information[44] (i.e. positive values) for the US data. It also makes sense from a practical point of view as we are trying to match the quarterly figures of BED data as a sum of monthly figures. In the case of Canada, however, the contemporaneous relationship appears to be quite strong and the impact of lags are either weak or in the wrong sign. As for the UK, the train-test exercise is not reassuring due to data properties, therefore it is difficult to infer a feasible lag structure from the results.

[44] This finding is robust to alternative specifications of window and test sizes.

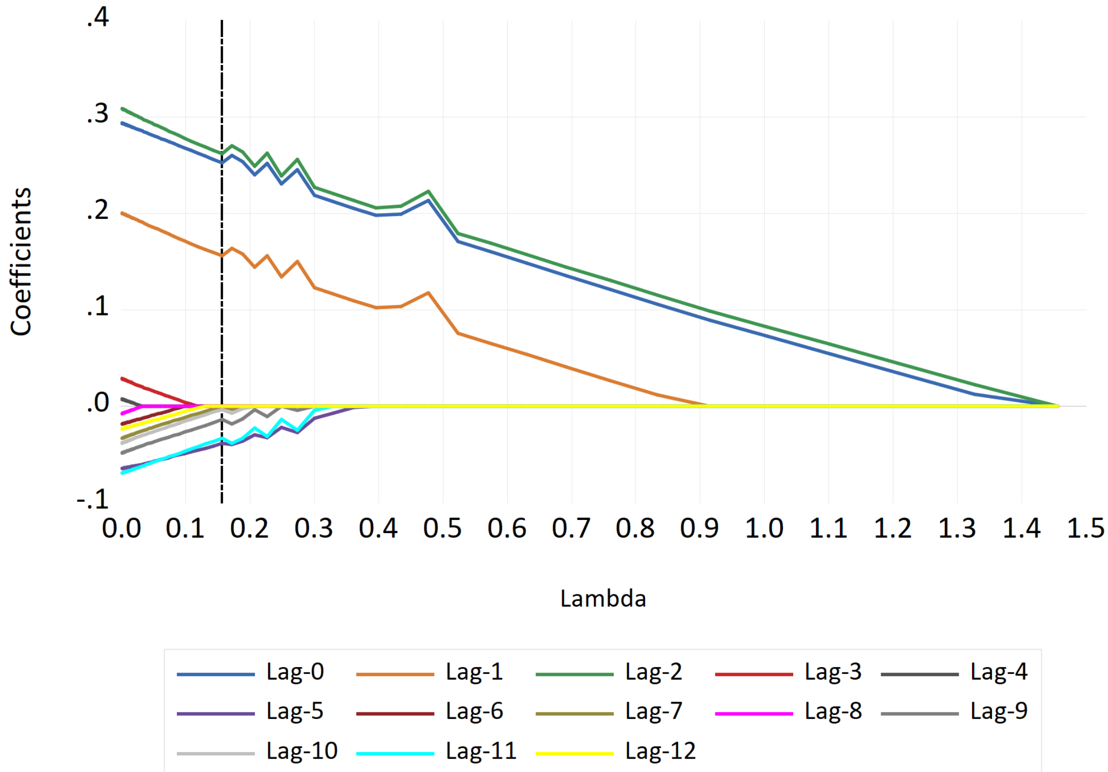


Figure 63: Coefficient evolution from LASSO regression estimation, US, 1–9 size class

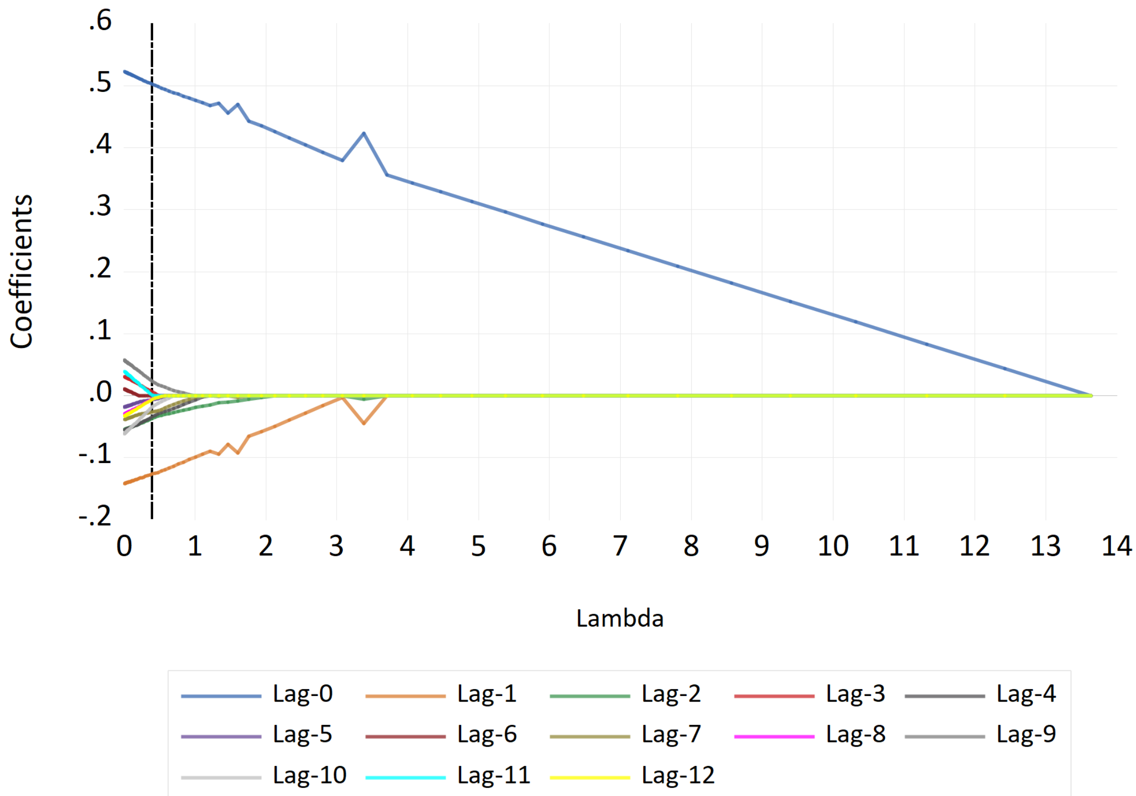


Figure 64: Coefficient evolution from LASSO regression estimation, CAN, 1–19 size class

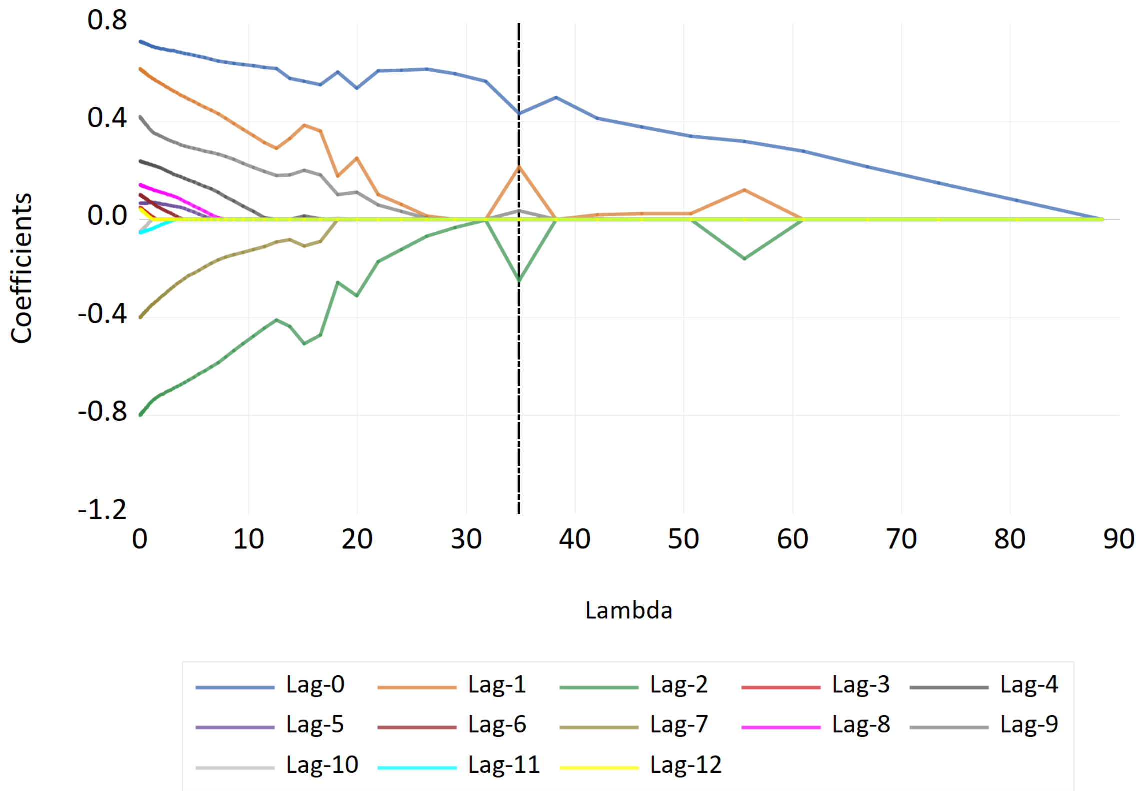


Figure 65: Coefficient evolution from LASSO regression estimation, UK, 1–9 size class