Time It Takes to Find a Worker: Estimating the Job Vacancy Fill Rate in Canada from 2015 to 2022

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I. Introduction

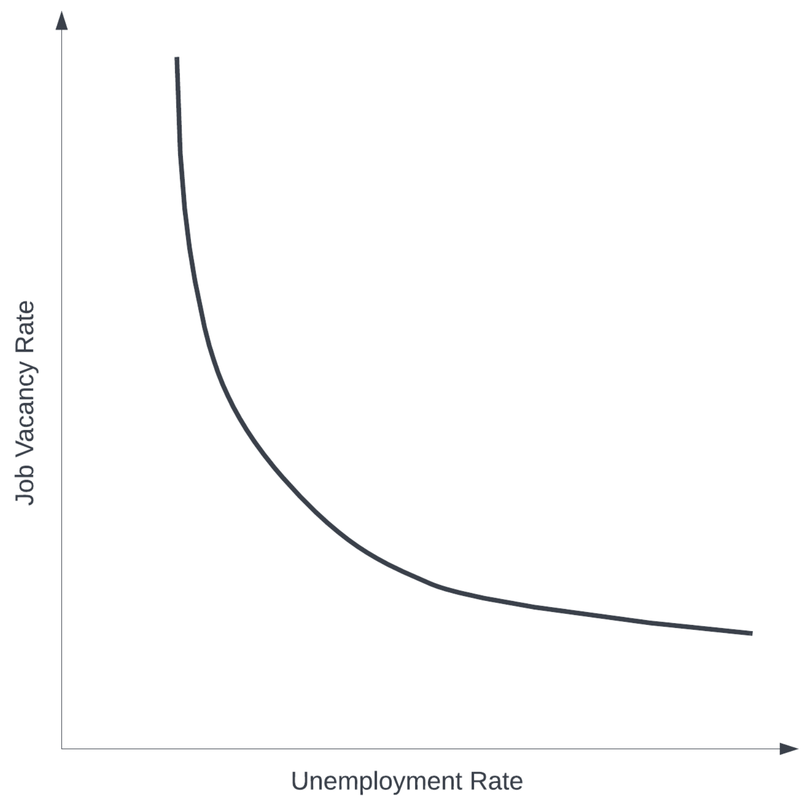
The length of time that it takes for an unemployed worker to find a job is a critical topic that concerns the welfare of labour market participants and the growth of an economy. The duration of a job vacancy is the other side of the coin. If there are many job vacancies in the economy that cannot obtain workers in a timely manner, the economy's productivity will be affected. The interaction between job vacancies and unemployment affects both the growth of an economy and the welfare of the labour force.

There has been a considerable amount of literature produced by labour economists and macroeconomists that studies the relationship between job vacancies and unemployment in an economy. The idea that job vacancies and unemployment coexist seems paradoxical. If employers are truly seeking to fill their vacancies, then there should be no unemployment, at least if involuntary job vacancies are greater than the number of unemployed. In a frictionless world, this should be the case; there can be either excess jobs or labour. Needless to say, the reality of the labour market is that the match between job seekers and employee seekers is never frictionless. What has been observed has been referred to as the Beveridge curve (or the “UV curve”): a downward sloping relationship between the job vacancy rate and the unemployment rate (see Graph 1).

The Beveridge curve has been observed around the world, including in the U.S. and European countries. The downward sloping curve should make intuitive sense. If the job vacancy rate is high, we can expect the unemployment rate to be low because more people are competing for a vacancy, making the filling of a position easier, and vice versa. This curve is one of the most important frameworks for understanding macroeconomics, like the Phillips curve (Elsby et al., 2015). The fact that the observed data points never lay on either axis suggests the presence of friction in the market.

The modelling device that economists use to capture the market outcome of transactions with search friction is the matching function (Petrongolo and Pissarides, 2001). While modelling the interaction between job seekers and employee seekers is not a trivial task, the matching function is rather simple. Despite their simplicity, a matching function can reveal veiled features of the labour market while being successful in fitting the observed data. The simplest (and common) matching function takes two arguments: unemployment and job vacancy.

Graph 1: The Beveridge curve



Using this modelling device, economists can explain a wide range of labour market phenomenon, including the negative relationship between the job vacancy rate and the unemployment rate captured by the Beveridge curve.

This paper has two research goals. First, I am going to estimate how the fill rate of job vacancies evolves over time. Second, I will examine the homogeneity assumption of the matching function. To achieve these objectives, I will construct a geometric sequence model that will allow me to estimate the age distribution of job vacancies. The data I am going to use has been obtained from the Statistics Canada website. The data is part of the Job Vacancy and Wage Survey (JVWS), a mandatory survey of Canadian businesses. I am going to use the vacancies duration data for this research. The model can be fitted to the JVWS data in various ways to achieve the research objectives. The model estimation identified a heterogenous fill rate across location and occupation of job vacancies, and the rate is declining from Q1 2015 to Q1 2022.

The rest of this paper will be organized as follows. In Section II, I will present a simple matching model that is going to be the basis of this research. Section III will provide a description of the data that this paper utilizes, and Section IV will explain the empirical methods that will be used to answer the research question presented earlier in this section. I will present the results obtained from this research along with my discussion in Section V. Section VI will conclude the paper.

II. Simple Model

Structurally modelling the interaction between job seekers and employee seekers is not a trivial task due to the friction and inefficiency present in the labour market. However, the complexity of reality does not discourage the usage of simple models. A matching function is a modelling device commonly used by economists to model the outcome of the interaction between both sides of the market. In this section, I am going to present a simple matching model that is the common foundation in labour market research literature. A simple model often requires strong assumptions, and the simple matching model I present in this section is not an exception. The interpretability and successfulness of a model rely on the validity of the assumptions employed. In this section, I am going to provide an introductory discussion of a simple matching function and the assumptions it employs.

Simplified Labour Market

The real-life labour market is infinitely complex; however, modelling the labour market requires a simplified market that resembles the one we see in the world. This paper will employ Mortensen and Pissarides style labour market presented by Blanchard and Diamond (1989), which is a simplified depiction of a decentralized labour market. On one side of the market, by definition, the labour force comprises either employed or unemployed workers, and unemployed workers are those who intend to work and are actively seeking a position. On the other side of the market, a job position can be filled, vacant, or idle. Idle jobs refer to unfilled positions that are not seeking to be filled.

In this paper, several basic assumptions are being made. The first assumption is that there is no “on-the-job search” for new positions. If one wishes to change their job voluntarily, they must separate from their position and enter unemployment. This is a strong assumption, since searching for a new position while on job is a very common practice. Nonetheless, this paper is going to maintain this assumption. This is because if an employee secures a new position while in their old position, the job switch will not be reflected in the aggregate data; thus, it will not be of concern in our model. The second assumption is that a job can only be filled by one worker, and a worker can only have one job. Finally, the third assumption is that the labour market is at its steady state.

A Simple Model

A simple form of a matching function $m(\cdot)$ can help us understand the outcome of matching between unemployed workers and job vacancies:

$$H = m(U, V)$$

where H is the number of new hires, U is the number of unemployed workers, and V is the number of job vacancies. For a perfectly frictionless labour market, $m(U, V) = \min(U, V)$. In this case, the observed relation between job vacancy and unemployment would be laying on the axes in Graph 1. In practice, the Cobb-Douglas form of the matching function, $m(U, V) = U^{\alpha}V^{\beta}$, $\alpha + \beta = 1$, is commonly used to approximate the matching outcome of the labour market with friction, and the function fits the data well (Petrongolo and Pissarides, 2001). Three assumptions about $m(\cdot)$ have been commonly employed in the literature (Pissarides, 2000). First, $m(\cdot)$ is assumed to be increasing in both U_t and V_t. This is intuitive: if either or both the number of unemployed workers and job vacancies increases, we can expect the number of matches (i.e., new hires) to increase.

Second, it is generally assumed that $m(\cdot)$ exhibits constant returns to scale (“CRS”). The CRS is a strong assumption; however, this assumption has been supported by empirical literature. Early work by Blanchard and Diamond (1990) has found that the return to scale is roughly constant or mildly increasing. Theoretically, a matching function that exhibits increasing returns to scale can produce multiple equilibria in the labour market at a steady state. Later empirical literature supports the finding that the modelled matching function mostly exhibits a CRS. (Petrongolo and Pissarides, 2001)

Third, $m(\cdot)$ is assumed to be homogenous of degree 1. This assumption implies the CRS assumption. Let θ denotes U/V, a measure of labour market tightness. If the function exhibits constant return, the probability of an unemployed worker finding a job, or the probability of a vacancy finding a worker, can be written as a function of market tightness. If we let q be the rate of the rate of vacancies being filled by unemployed workers, then:

$$q = \frac{m(U,V)}{V} = m(\theta^{-1}, 1) = q(\theta)$$

We can see that $q'(\theta) < 0$, which suggests that when the market is tight, it is easier for a firm to fill its vacancies. This result conforms with our expectations about the labour market reality.

Homogeneous and Constant Fill Rate

There are two implied assumptions with respect to the matching function: a homogeneous and a constant fill rate of job vacancies. First, the rate of job vacancy filling is the same for each vacancy and independent of job characteristics. If the homogeneity assumption is viable, the fill rate should not depend on the type of job vacancy characteristics; the rate for the financial industry (for example) should be the same as for, say, the cultural industry, if they are homogenous. Homogeneity is a strong assumption which will be a subject of examination in this paper. The second assumption I refer to above is that the fill rate is constant over the modelled period. This is a necessary assumption to be made when we are modelling the labour market using the matching function.

In this section, I provided a brief introduction to a simple matching model. The discussed model is sufficient in modelling the Beveridge curve because it demonstrates the negative relationship between the rate of job vacancy and unemployment.[1]

III. Data

Data Source

The dataset that I am relying on for this research paper is "Job vacancies, proportion of job vacancies and average offered hourly wage by occupation and duration of job vacancy, quarterly, unadjusted for seasonality (Table 14-10-0328-03)" ("the dataset" or "data" hereafter) published by Statistics Canada (2022). This data was downloaded on July 15, 2022. It contains quarterly data regarding Canadian job vacancies: the number, the duration, the location of the province, and the occupation, dating from Q1 2015 to Q1 2022.

This dataset is a product of the monthly government sample survey, and the Job Vacancy and Wage Survey (JVWS), conducted by Statistics Canada. The survey targets all businesses with more than one employee operating in Canada. The data is collected quarterly using a stratified sampling of approximately 100,000 businesses. The survey is delivered via email or

[1] Let ϕ be the rate at which the job separation occurs. This separation can be due to either employees quitting, getting fired, or the position being abolished. Let L denote the size of the labour force. The inflow of workers from employment to unemployment will be $\phi(L-U)$. Since the rate at which unemployed workers find jobs is $a(\theta) = \frac{m(U,V)}{U}$, the unemployment outflow will be $a(\theta)U$. An economy at steady state means a constant rate of unemployment, which means that the outflow and inflow of labour from and to unemployment is equal; therefore, $\phi(L-U) = a(\theta)U$. This equation can be rearranged as $u = \frac{\phi}{a(\theta)+\phi}$ since $U \equiv uL$.

mail, in English or French, and the selected businesses are legally obligated to complete the survey (Statistics Canada, "Job Vacancy and Wage Survey (JVWS)").

Variables

The dataset contains the number and characteristics of job vacancies in each quarter. There are three characteristics recorded in the dataset: the province of the job vacancies, the National Occupational Classification of the job vacancies, and the duration (i.e., age) of the job vacancies. For the provinces, I only retain the six most populous in Canada: Ontario, Quebec, British Columbia, Alberta, Manitoba, and Saskatchewan. The age of the job vacancy is grouped by

- all durations
- less than 15 days
- 15 to 29 days
- 30 to 59 days
- 60 to 89 days, and
- 90 days or more.

One needs to mention that the *all duration* group contains more job vacancies than the aggregate of the groups that follow before 2020. This is because the group contains job vacancies that are constantly recruiting; however, starting in Q1 2020, the survey separates the question for the number of constantly recruiting vacancies from the job vacancy duration question. At the same time, the duration question splits *90 days or more* into two groups:

- 90 to 119 days, and

- 120 days or more. [2]

Note that the data for Q2 2020 and Q3 2020 is missing.

Descriptive Statistics

The average vacancy age distribution is plotted in Graph 3.1. As we can see, as an age category gets older, its vacancy number decreases. Vacancy age groups that end with infinity (i.e., groups that are "## days or more") have the highest numbers of vacancies. For example, the "120 days or more" age group (aka. "a120binf") has the highest number of vacancies.

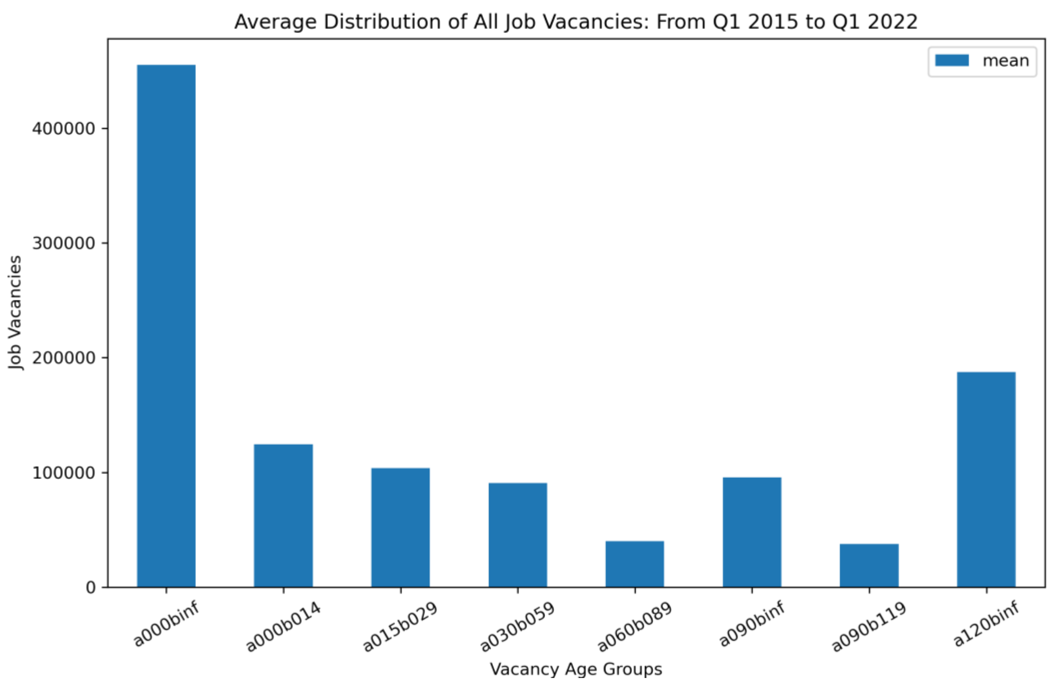
The total number of vacancies (except those that are constantly recruiting) are plotted in Graph 3.2. As we can see, there is an increasing number of vacant jobs in Canada. This increase is modest before 2020, and then there is a sharp increase in vacancies after 2020. I attribute this dramatic increase in job vacancies to the COVID-19 pandemic. We can see a cyclical pattern in the vacancies: the numbers tend to be higher in the middle of a year and lower at the beginning/end of a year.

Graph 3.3 illustrates the growth in job vacancies by provinces. As we can see, Ontario consistently has the highest number of job vacancies. Quebec, British Columba, and Alberta all had a similar number of vacancies in 2015; however, their numbers diverge in later years. Manitoba and Saskatchewan have had a relatively steady number of job vacancies. This might be due to the fact that the natural-resource-based industries are the main production activity in both provinces (Government of Manitoba, "Manitoba's Strategic Advantages"; Government of Saskatchewan, "Economic overview"), which may be less affected by the pandemic. Graph 3.4

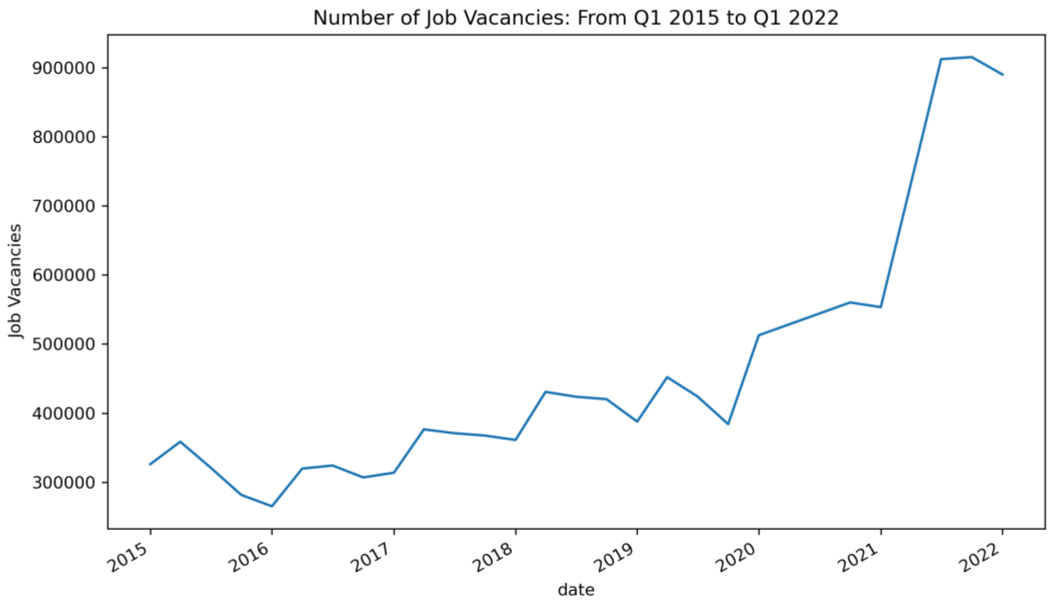
[2] In later parts of this paper, I might refer to each age group using "a###b###" format (e.g., for age 90 to 119 days, the formatted writing will be "a090b119". For age groups ending in time infinity, it will be formatted as "a###binf").

graphs the growth in job vacancies by occupation. The *Sales and Service* occupation has by far the highest number of vacancies, followed by the *Trades, Transport and Equipment Operators and Related industry*, and the *Business, Finance and Administration* occupation. The *Health* industry occupation had a steady number of vacancies before 2020, and then it experiences strong growth after.

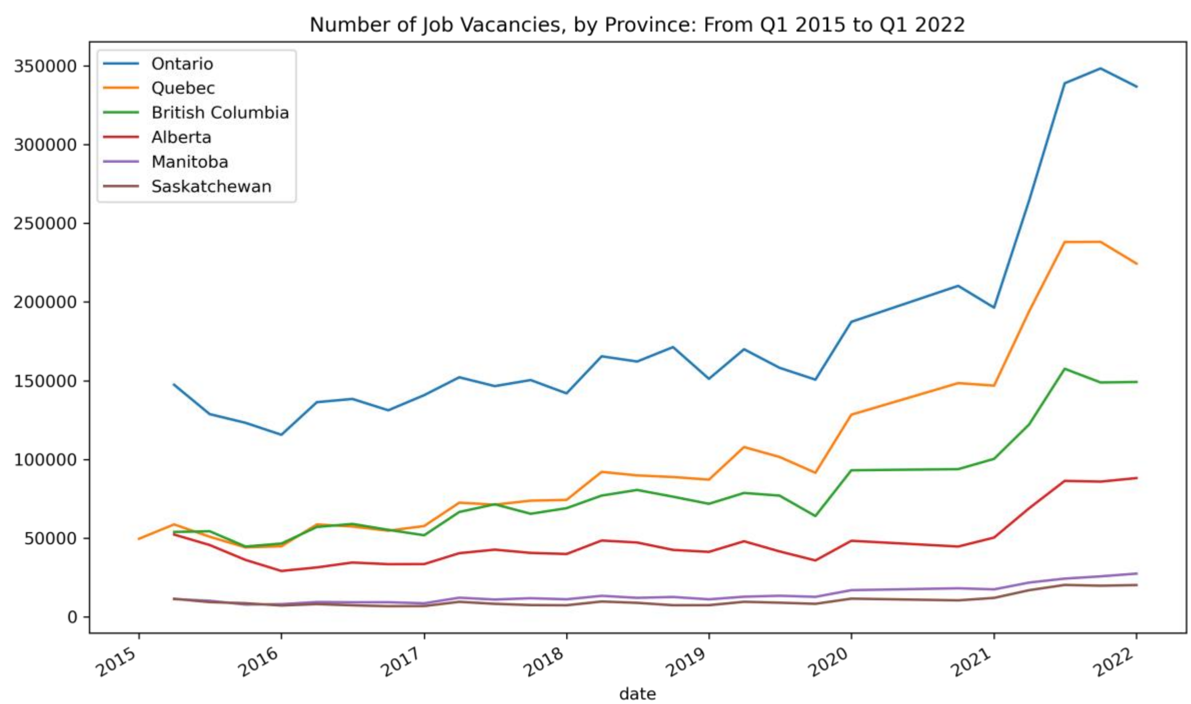
Graph 3.1: Average Age Distribution of Job Vacancies from Q1 2015 to Q1 2022



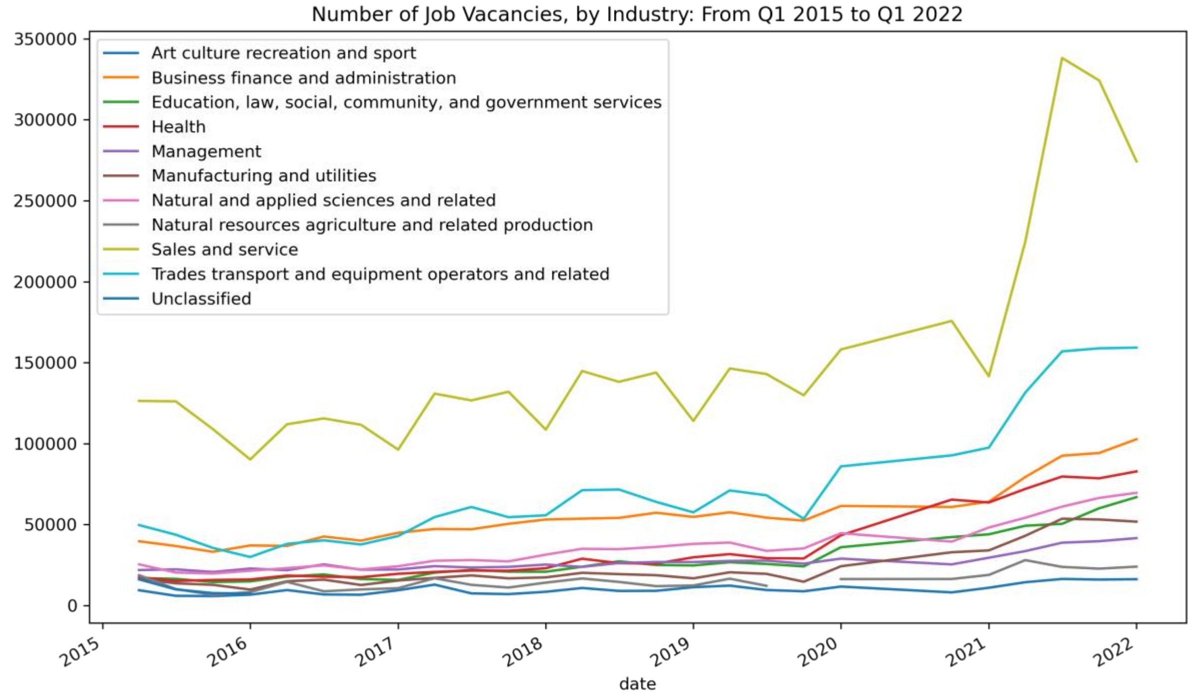
Graph 3.2: Number of Job Vacancies from Q1 2015 to Q1 2022



Graph 3.3: Number of Job Vacancies from Q1 2015 to Q1 2022, by province



Graph 3.4: Number of Job Vacancies from Q1 2015 to Q1 2022, by occupation



IV. Empirical Method

This paper attempts to examine the homogeneity of q and research the evolution of q over time. The basic approach to testing the homogeneity is to compare the estimated daily probability of a vacant position being filled between different job characteristics. If the homogeneity assumption is viable, we can expect the probability to be identical for vacancies in different industries and provinces. We can research the evolution of q by conducting estimation quarterly or yearly and see how q changes over time. This paper is going to use the data described in Section III, which contains the observed distribution of the age of job vacancies. We can construct a geometric sequence from the matching function and transform the sequence into a geometric series that will model the number of job vacancies in the age distribution between two ages.

The simple matching function described in Section II is:

$$H = m(U, V)$$

I will maintain the assumptions presented in Section II. The Poisson arrival rate of any one vacant position being filled would be the number of new hires divided by the number of job vacancies. Let q denote the daily Poisson arrival rate of a vacancy being filled:

$$q(U, V) = \frac{m(U, V)}{V}$$

If the homogeneity assumption is viable, q should be identical for all jobs.

With q found definitionally, the age distribution of the job vacancies can be modelled using a geometric sequence. Let V_0 denote the inflow rate of new job vacancies. The creation of a new job vacancy can be the result of either the worker being separated from a position, or if a position has just been created. The steady state implies that the economy is at its equilibrium; therefore, we can model the economy with a constant number of unemployed workers and a constant number of job vacancies. Since there would be a steady outflow of workers being separated from their positions (and thus the positions become empty,) the vacancy inflow would be constant over time as well. With a constant V_0 and q, one can model the age distribution of job vacancies as a function of time:

$$v(t) = V_0(1 - q)^t$$

where $v(t)$ is the number of job vacancies that are t days old. As we can see, when the age of vacancies, t, increases, the number of vacancies decreases. This is intuitive: the probability that a job vacancy will survive (i.e., not be filled) until the next day is $1 - q$, and so the total number of vacancies in the market decreases in an exponential manner. The total number of job vacancies of a time interval between age a and b days old can be modelled by using the geometric series of $v(t)$:

$$V(a,b) = \sum_{t=a}^{b} v(t) = \frac{V_0(1-q)^a(1-(1-q)^b)}{q}$$

Fitting the data using $V(a,b)$ can allow us to estimate V_0 and q. The goal of this paper is to estimate q using the vacancy duration data described in the previous section that is $V(a,b)$.

We can see that the model $V(a,b)$ is a nonlinear function; it requires using a nonlinear method of fitting the observed data. This paper employs the Nonlinear Least Squares method, which finds the optimal parameters by minimizing the squared residual of the model. The computational process would yield an optimal V_0 and q value that minimizes the squared difference between the model and the observation.

The evolution of q will be studied in the following ways. I will list three possible fitting time durations: the entire duration of the observation (i.e., from Q1 2015 to Q1 2022), the yearly duration, and the quarterly duration. For the entire duration, I will do one that fits all observations. For the yearly duration, I will fit one model for each year. For the quarterly duration, I will fit one model for each quarter.

For examining the homogeneity assumption, I will fit observations for the different industries and provinces separately. A homogenous job vacancy fill rate would yield a uniform daily probability of the position being filled; therefore, examining q for different industries and provinces would allow one to see the validity of the homogeneity assumption.

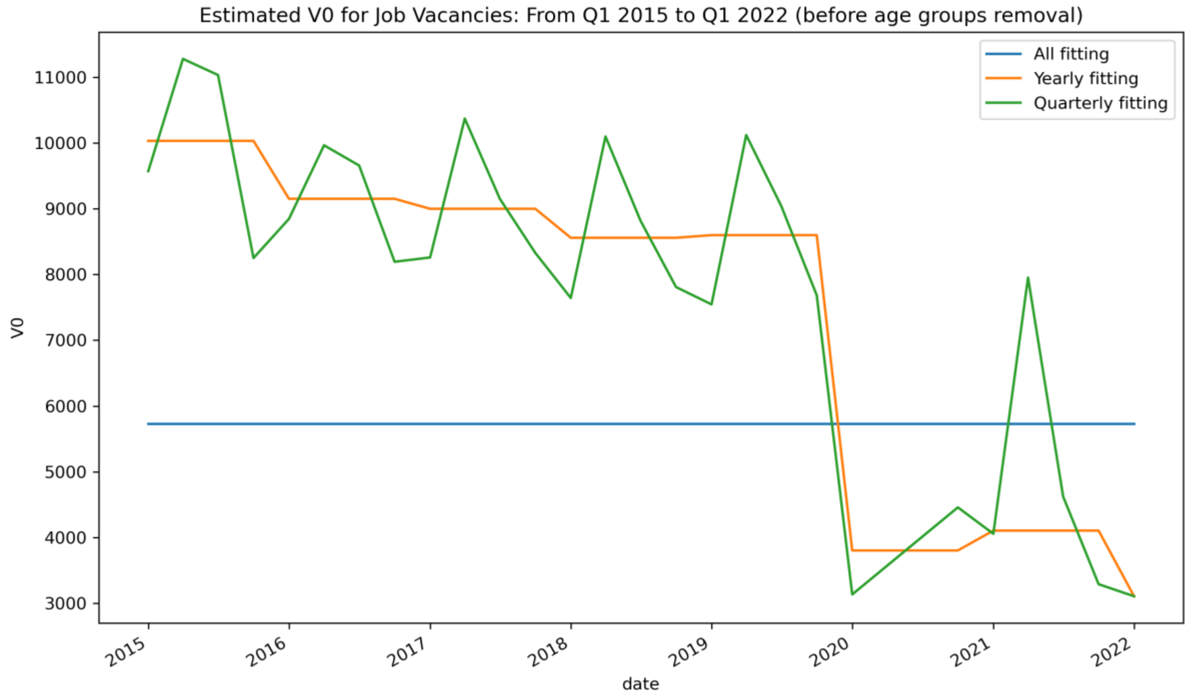
V. Result and Discussion

This section has two parts. First, I am going to demonstrate how I estimated q over time in the Canadian labour market. Second, I am going to demonstrate how I tested the homogeneity assumption of job vacancy fill rate. The results presented in this section were obtained using Python codes, and the data and the Jupyter Notebook file that is being used to estimate V_0 and q is archived in a GitHub repository and can be accessed via https://github.com/YanliangZhu/MAPaper.

Evolution of q

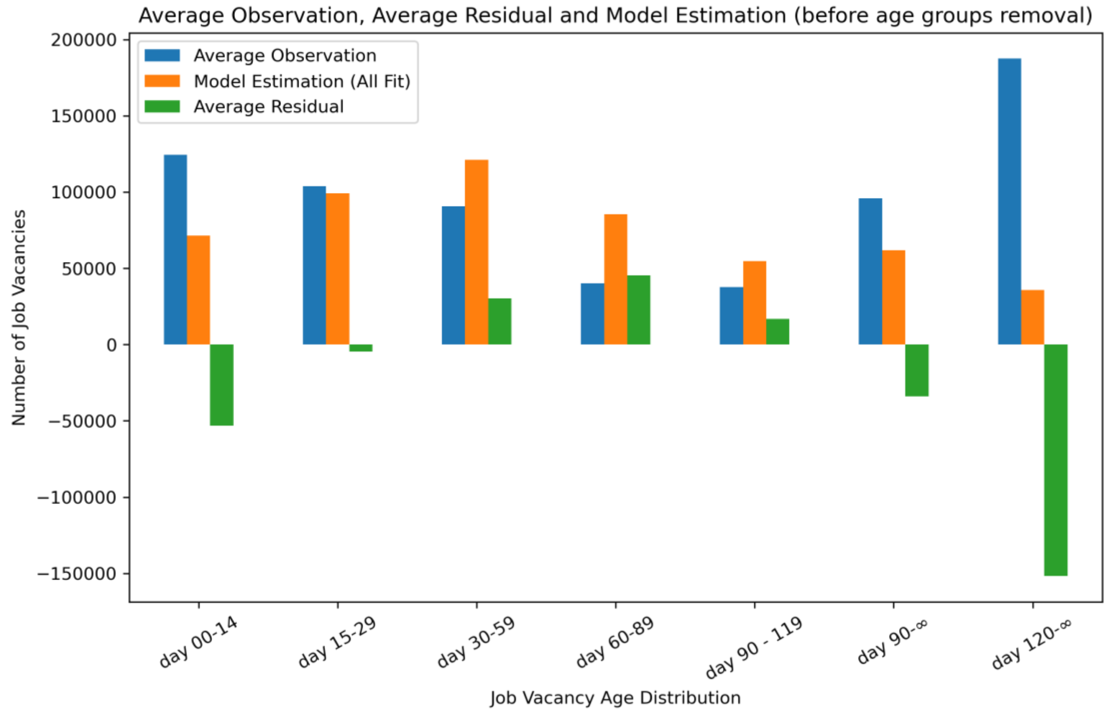
One of the assumptions about the labour market is that the q is constant during the modelled period of time, and this assumption is required for the geometric series model $V(a,b)$; therefore, selecting a fitting duration for a model is an important modelling decision. As stated in Section IV, there are three ways of fitting the data using model $V(a,b)$: one fitting for the entire observation period (one fitting, "all fitting"), one fitting for each year (eight fittings, "yearly fitting"), and one fitting for each quarter (27 fittings, "quarterly fitting"). Graph 5.1a and Graph 5.1b plot the $V0$ and q estimated using all three ways of fitting, respectively. The yearly fitting and the quarterly fitting illustrate a labour market with a steady decrease of $V0$ and q before 2020, and a sharp drop in both $V0$ and q after 2020. The $V0$ estimated in the quarterly fitting exhibits a strong seasonal cycle, with high job vacancies estimated during the middle of the year. The result suggests that the yearly fitting is a good fitting duration to study how q evolves over the years, since the seasonal effect is absent.

Graph 5.1a: Yearly, quarterly, and all fittings of V_0 from Q1 2015 to Q1 2022, before removing *a090binf* and *a120binf*



Graph 5.1b: Yearly, quarterly, and all fittings of q from Q1 2015 to Q1 2022, before removing *a090binf* and *a120binf*

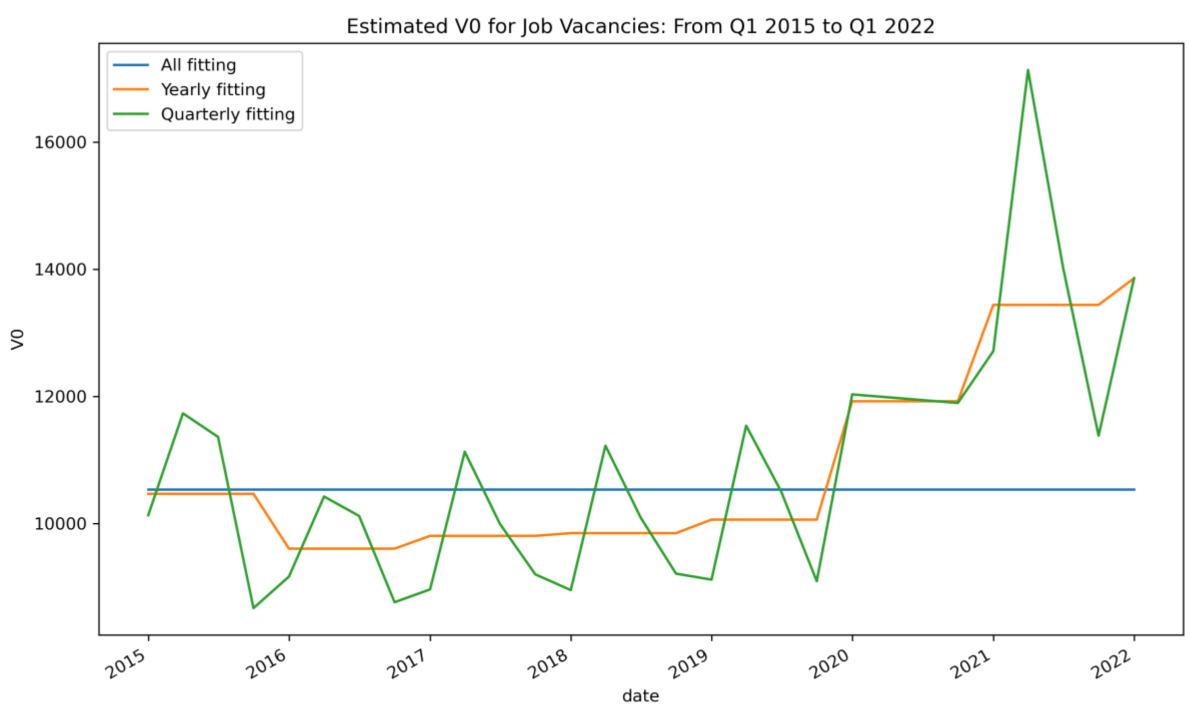
Graph 5.1c: Average Observation and The Model Estimation (All Fit), before removing *a090binf* and *a120binf*



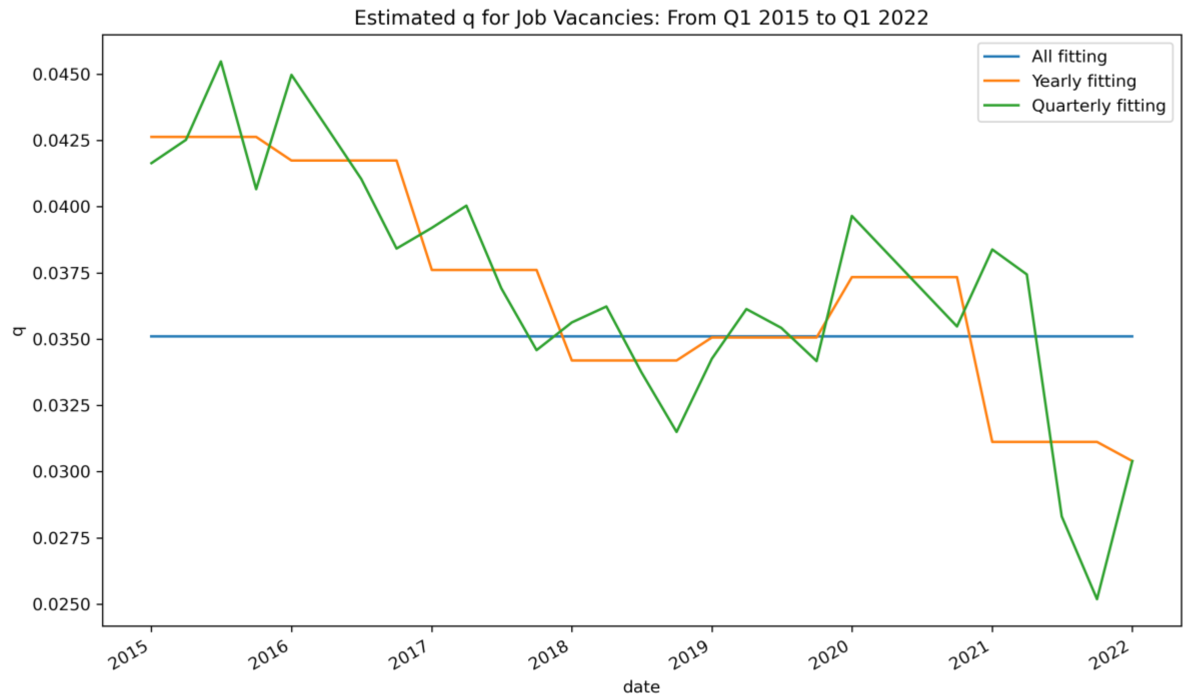
A closer look at the model residuals, however, warrants caution in accepting the fittings depicted in Graph 5.1.a and Graph 5.1.b. Graph 5.1.c plots the average observations against the all-fitting model and the average residuals. As we can see, there are large negative residuals associated with the vacancy age groups that end with time infinity (i.e., 90 days or more and 120 days or more age groups). Similar results can be found on yearly fittings and quarterly fittings. Appendix I summarizes the residuals. This may be because these groups contain the vacancy inflow from previous periods. The model estimates the age distribution of vacancies resulting from the current quarter; however, any vacancies older than 91 days (the number of days in a quarter) are most definitely from the vacancies inflow of the last quarter. Therefore, a new fitting is required to estimate a more accurate $V0$ and q.

I removed the data points from age groups *90 to 119 days*, *90 days or more* and *120 days or more,* and refitted the model. Graph 5.2a and Graph 5.2b plot the estimated $V0$ and q. As we can see, the model estimates a higher number of job vacancies compared to the fittings before removing the age groups. The number of vacancies, in fact, held steady before 2020 and experienced a sharp increase during and after 2020. The estimated q was on the decline before 2018 and held steady from 2018 to 2020. It then experienced a sharp drop in 2021. Graph 5.2.c plotted the average observations against the all-fitting model and the average residuals after removing age group *a090binf* and *a120binf*. We can see the residuals associated with each age group are significantly smaller compared to the fitting depicted in Graph5.1c. Table 5 summarizes the goodness of fit statistics of the model before and after the removal. The standard error decreased despite fewer data points.

Graph 5.2a: Yearly, quarterly, and all fittings of vacancy flows from Q1 2015 to Q1 2022



Graph 5.2b: Yearly, quarterly, and all fittings of q from Q1 2015 to Q1 2022



Graph 5.2c: Average Observation and The Model Estimation (All Fit)

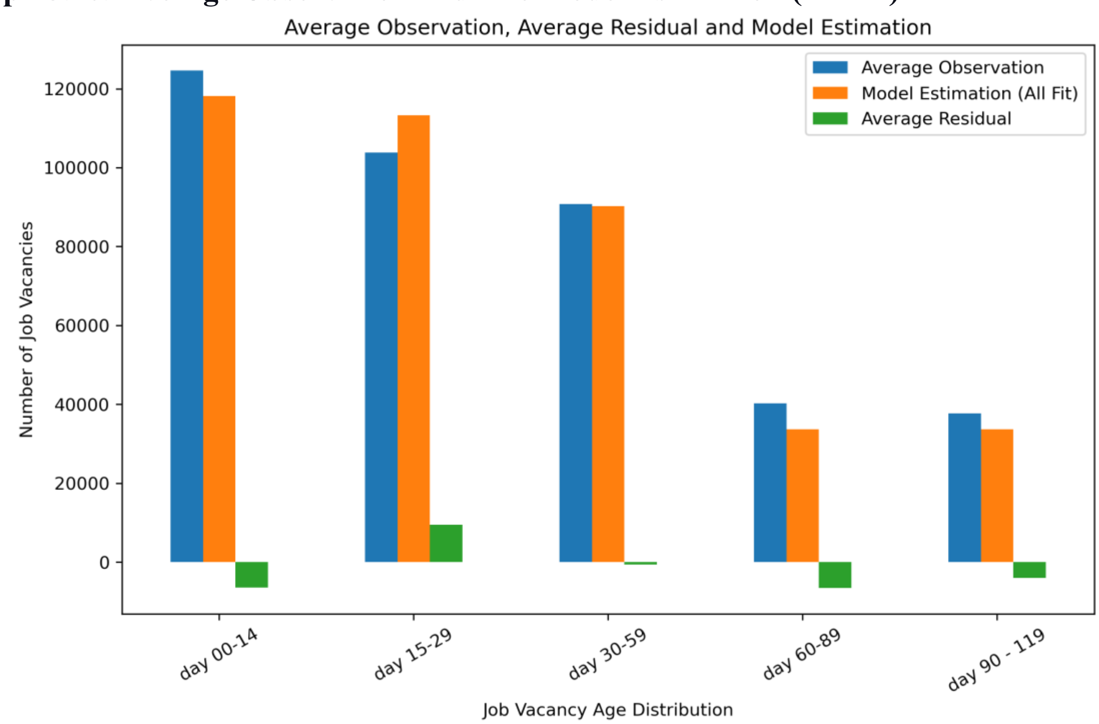


Table 5: The goodness of fit statistics before and after the removal of age group *a090binf* and *a120binf*

	Before Removal	After Removal
Est. V_0	5726.08458	10532.7849
(Standard Error)	(647.965830)	(478.257469)
Est. q	0.01803193	0.03510477
(Standard Error)	(0.00154864)	(0.00133182)
Number of Data Points	149	115
AIC	3317.04895	2353.84906
BIC	3323.05684	2359.33892

I attribute the large difference in the estimated q and $V0$ before and after the removal of the age groups to the COVID-19 pandemic. In the pre-pandemic time, the labour market was relatively steady with no major shock; however, the large shock of the pandemic on the labour market amplified the "carrying the previous quarter vacant jobs" issue, resulting in the large differences in estimations after 2020. The residuals are summarized in Appendix II.

Declining q

From Graph 5.2a and 5.2b, we can observe a relatively steady $V0$ and decreasing q before 2020, and from Graph 3.2, we can see that the total number of job vacancies were increasing at the same time. If we check the Canadian unemployment rate, it was on the decline from 6.9% in 2015 to 5.7% in 2019 (World Bank, "Unemployment, total (% of total labor force) (modeled ILO estimate) - Canada"). I attribute the declining q to the congestion effect. Recall in Section II, I discussed how q can be expressed as a function of market tightness, $\theta \equiv \frac{U}{V}$, and that $q'(\theta) < 0$. An increasing number of job vacancies will produce marginally fewer matches between unemployed worker and vacant jobs; it was harder for a firm to fill their vacancy if there were more vacancies on the market. Since q is the rate of a vacancy being filled, a smaller

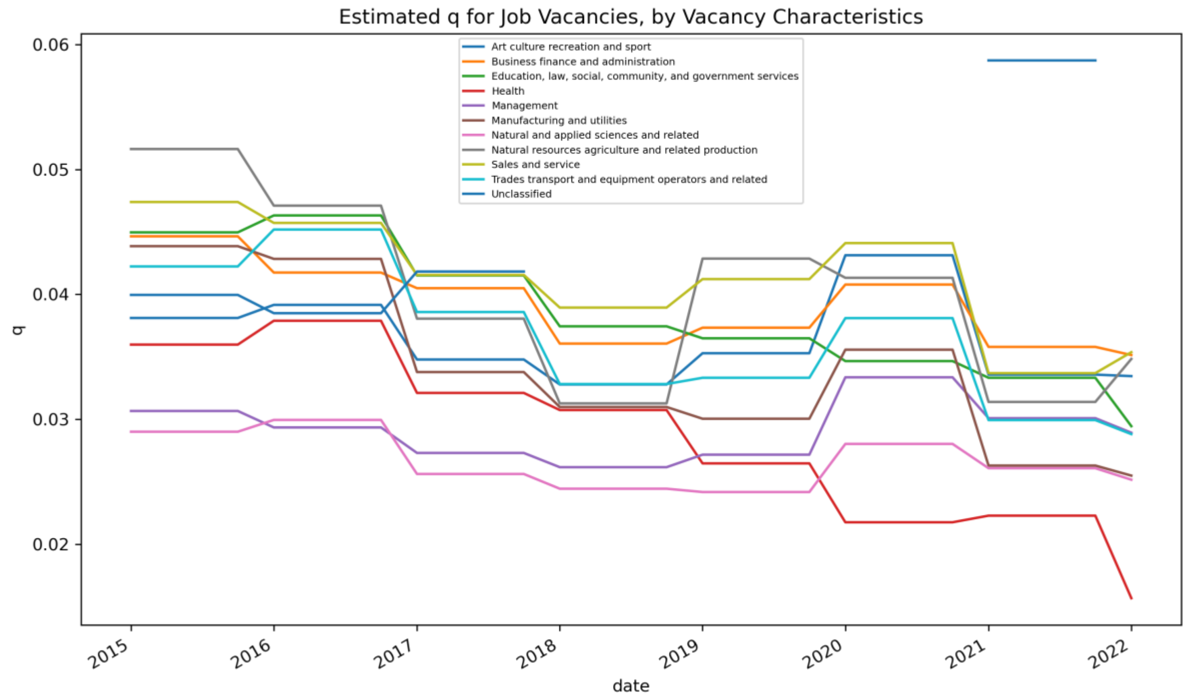
q would suggest a longer average vacancy duration; therefore, we can conclude that, before 2020, while the estimated inflow of new job vacancies remains relatively constant, the average vacancy duration became longer, and the number of total job vacancies increased. This paints a picture of a labour market facing congestion.

Homogeneity Assumption

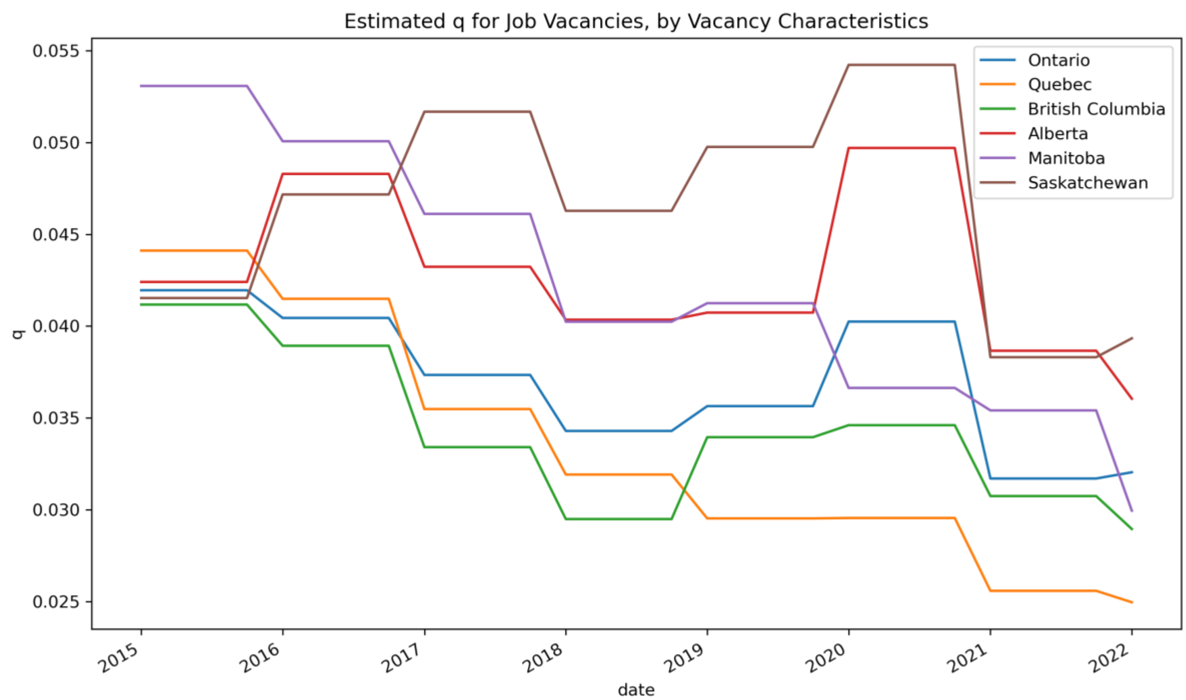
If the homogeneity assumption holds true, the estimated q would be uniform across job characteristics (occupation and province). I conducted a yearly fitting using datasets containing only one characteristic's observed vacancies. There is a total of 17 datasets, of which 6 are individual provinces and 11 are individual industries. Graphs 5.3a and 5.3b plot the estimated q by the occupation and the province, respectively. As we can see, it is difficult to conclude the homogeneity of q across different industries and provinces. The heterogenous q we estimated strongly suggests that the homogeneity assumption does not hold.

That q is heterogeneous across the provinces and the occupations is not a surprising result. Van Ours and Ridder (1991) found that a longer vacancy duration is associated with a higher required education level. I selected *management* (high skill), *Natural and applied sciences and related* (high skill), *Trades transport and equipment operators and related* (low skill), and *Natural resources agriculture and related production* (low skill) occupations from my estimations. Graph 5.3c plots the selected occupations from 2015 to 2019 (pre-COVID). As we can see, the lower-skill occupations have a larger q than those requiring high-skilled labour, and therefore, they have a comparatively shorter vacancy duration. This might be because high-skill occupations are also associated with higher training costs; therefore, firms tend to be more cautious when hiring (Oyer and Schaefer, 2011). Despite having a heterogeneous fill rate of vacant jobs, the model still performed well.

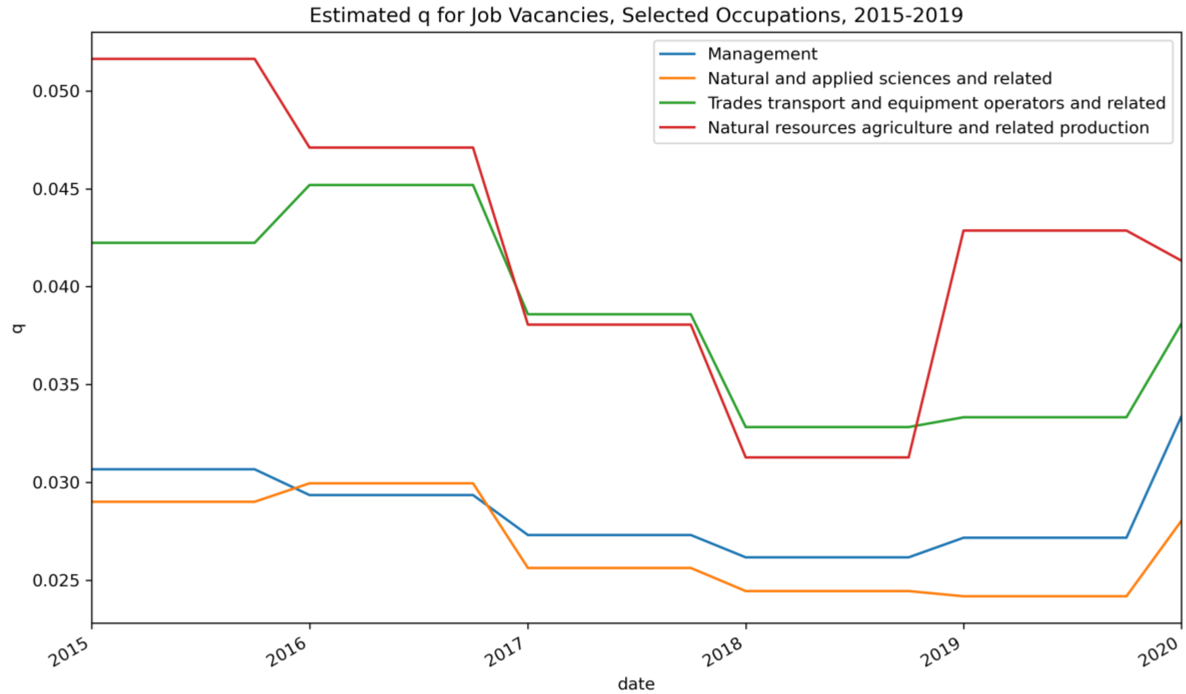
Graphs 5.3a: Estimated *q* from Q1 2015 to Q1 2022, by occupation



Graphs 5.3b: Estimated *q* from Q1 2015 to Q1 2022, by province



Graph 5.3c: Estimated *q* for selected occupations, from 2015 to 2019



VI. Conclusion

In this paper, I have summarized common assumptions that economists make when modelling the matching outcome of the labour market between job vacancies and unemployed workers. Such modelling uses the matching function, which takes the number of unemployed workers and job vacancies as its arguments. The matching function, despite its simplicity, plays a key role in modelling the negative relationship between job vacancy and unemployment in the market.

Based on the conceptual definitions derived from the matching function, this paper constructs a geometric sequence that captures the distribution of the age of job vacancies. From this sequence, I designed a geometric series that has allowed me to model the number of job vacancies in an age range. Fitting the Canadian labour market data using the model, I estimate a declining q, the job vacancy fill rate, and a relatively constant V_0, the inflow of job vacancies, from 2015 to 2019. I attribute this trend to the congestion effect. After Canada faced the COVID-19 pandemic, q dropped sharply, and V_0 dramatically increased.

Like all other simple models using aggregate inputs, this model employs strong assumptions that require justification and verification. The homogeneity assumption of job vacancy fill rate is one of them; however, my model estimation cannot support the homogeneity assumption. I demonstrate a heterogenous q for different industries and provinces; therefore, I concluded that the homogenous assumption does not hold true.

Future research in the matching behaviour of the Canadian labour market should focus on the cause of the changing q and V_0, especially in the context of matching efficiency. The matching efficiency is not directly observable, and so the methodological development in efficiency estimation would be important for future research.

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Appendix I

Appendix I Table: Observation, Model, and Residuals. Before Removing the Age Groups *a090binf* and *a120binf*

		Observation							Residuals							Model			
									All Fit										
year	**quarter**	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090binf***	***a090b119***	***a120binf***	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090binf***	***a090b119***	***a120binf***	V_0	***q***	**BIC**	**AIC**
2015	1	113260	83630	64160	25115	39830			-41845.5	15476.17	56930.08	60358.53	21911.65			5726.085	0.018032	3323.057	3317.049
2015	2	126345	102280	68450	22310	39165			-54930.5	-3173.83	52640.08	63163.53	22576.65						
2015	3	121925	87780	58290	21275	31790			-50510.5	11326.17	62800.08	64198.53	29951.65						
2015	4	96690	75190	57310	21110	31200			-25275.5	23916.17	63780.08	64363.53	30541.65						
2016	1	98600	71795	48650	16660	29350			-27185.5	27311.17	72440.08	68813.53	32391.65						
2016	2	113035	87695	59525	21595	37780			-41620.5	11411.17	61565.08	63878.53	23961.65						
2016	3	111330	89330	64380	23200	35870			-39915.5	9776.17	56710.08	62273.53	25871.65						
2016	4	99275	80880	64735	24525	37425			-27860.5	18226.17	56355.08	60948.53	24316.65						
2017	1	100235	82725	62370	24125	44190			-28820.5	16381.17	58720.08	61348.53	17551.65						
2017	2	123895	99145	76490	25875	51040			-52480.5	-38.8297	44600.08	59598.53	10701.65						
2017	3	115040	94575	81310	29830	50170			-43625.5	4531.17	39780.08	55643.53	11571.65						
2017	4	105970	96565	81620	33075	50235			-34555.5	2541.17	39470.08	52398.53	11506.65						
2018	1	105460	85690	77730	31165	61075			-34045.5	13416.17	43360.08	54308.53	666.6532						
2018	2	131070	106870	93545	37965	61300			-59655.5	-7763.83	27545.08	47508.53	441.6532						
2018	3	118755	106225	92915	41265	64560			-47340.5	-7118.83	28175.08	44208.53	-2818.35						
2018	4	109860	101830	98895	40675	68900			-38445.5	-2723.83	22195.08	44798.53	-7158.35						
2019	1	107765	92120	84130	34600	69105			-36350.5	6986.17	36960.08	50873.53	-7363.35						
2019	2	133425	112230	96610	37345	72430			-62010.5	-13123.8	24480.08	48128.53	-10688.3						
2019	3	121170	105905	90105	35695	71220			-49755.5	-6798.83	30985.08	49778.53	-9478.35						
2019	4	107615	92770	82760	36390	64505			-36200.5	6336.17	38330.08	49083.53	-2763.35						
2020	1	141330	96630	85765	42750	146285	23220	123070	-69915.5	2476.17	35325.08	42723.53	-84543.3	31439.51	-87301.6				
2020	4	142440	109620	107585	51560	149010	26115	122895	-71025.5	-10513.8	13505.08	33913.53	-87268.3	28544.51	-87126.6				
2021	1	148945	109325	95515	50095	149600	22655	126945	-77530.5	-10218.8	25575.08	35378.53	-87858.3	32004.51	-91176.6				
2021	2	200195	152400	139565	64030	175715	31525	144185	-128780	-53293.8	-18474.9	21443.53	-113973	23134.51	-108417				
2021	3	160135	178810	184600	97440	291595	51310	240290	-88720.5	-79703.8	-63509.9	-11966.5	-229853	3349.511	-204522				
2021	4	135850	151660	178815	105960	343260	58010	285250	-64435.5	-52553.8	-57724.9	-20486.5	-281518	-3350.49	-249482				
2022	1	173840	149430	156055	90075	320985	51250	269740	-102425	-50323.8	-34964.9	-4601.47	-259243	3409.511	-233972				
									Yearly Fit										
year	**quarter**	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090binf***	***a090b119***	***a120binf***	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090binf***	***a090b119***	***a120binf***	V_0	***q***	**BIC**	**AIC**
2015	1	113260	83630	64160	25115	39830			-4318.5	9793.571	1720.094	-4659.82	-33729.7			10031.83	0.040357	392.1903	390.1989
2015	2	126345	102280	68450	22310	39165			-17403.5	-8856.43	-2569.91	-1854.82	-33064.7						
2015	3	121925	87780	58290	21275	31790			-12983.5	5643.571	7590.094	-819.819	-25689.7						
2015	4	96690	75190	57310	21110	31200			12251.5	18233.57	8570.094	-654.819	-25099.7						
2016	1	98600	71795	48650	16660	29350			1464.817	16095.23	14950.38	3878.745	-22986.7			9151.389	0.039229	389.4345	387.443
2016	2	113035	87695	59525	21595	37780			-12970.2	195.2281	4075.377	-1056.26	-31416.7						
2016	3	111330	89330	64380	23200	35870			-11265.2	-1439.77	-779.623	-2661.26	-29506.7						
2016	4	99275	80880	64735	24525	37425			789.817	7010.228	-1134.62	-3986.26	-31061.7						
2017	1	100235	82725	62370	24125	44190			1493.173	17602.88	20074.43	8132.081	-32124.2			8999.155	0.033796	399.6336	397.6421
2017	2	123895	99145	76490	25875	51040			-22166.8	1182.881	5954.427	6382.081	-38974.2						
2017	3	115040	94575	81310	29830	50170			-13311.8	5752.881	1134.427	2427.081	-38104.2						
2017	4	105970	96565	81620	33075	50235			-4241.83	3762.881	824.4274	-817.919	-38169.2						
2018	1	105460	85690	77730	31165	61075			-5706.64	23754.18	23687.65	16324.62	-39757.5			8558.213	0.028837	407.7085	405.717
2018	2	131070	106870	93545	37965	61300			-31316.6	2574.18	7872.654	9524.619	-39982.5						

Time It Takes to Find a Worker

2018	3	118755	106225	92915	41265	64560			-19001.6	3219.18	8502.654	6224.619	-43242.5						
2018	4	109860	101830	98895	40675	68900			-10106.6	7614.18	2522.654	6814.619	-47582.5						
2019	1	107765	92120	84130	34600	69105			-7642.08	17358.89	16928.94	12450.19	-48110.7			8598.276	0.028994	411.6812	409.6897
2019	2	133425	112230	96610	37345	72430			-33302.1	-2751.11	4448.936	9705.189	-51435.7						
2019	3	121170	105905	90105	35695	71220			-21047.1	3573.891	10953.94	11355.19	-50225.7						
2019	4	107615	92770	82760	36390	64505			-7492.08	16708.89	18298.94	10660.19	-43510.7						
2020	1	141330	96630	85765	42750	146285	23220	123070	-91917.5	-17575.4	29353.47	62668.12	-31056.5	63174.96	-41809.4	3802.723	0.011574	309.8557	308.5776
2020	4	142440	109620	107585	51560	149010	26115	122895	-93027.5	-30565.4	7533.465	53858.12	-33781.5	60279.96	-41634.4				
2021	1	148945	109325	95515	50095	149600	22655	126945	-94648.2	-16923.3	49969.4	99537.08	61363.34	114532.1	34928.53	4104.825	0.00879	638.9924	636.328
2021	2	200195	152400	139565	64030	175715	31525	144185	-145898	-59998.3	5919.4	85602.08	35248.34	105662.1	17688.53				
2021	3	160135	178810	184600	97440	291595	51310	240290	-105838	-86408.3	-39115.6	52192.08	-80631.7	85877.07	-78416.5				
2021	4	135850	151660	178815	105960	343260	58010	285250	-81553.2	-59258.3	-33330.6	43672.08	-132297	79177.07	-123376				
2022	1	173840	149430	156055	90075	320985	51250	269740	-132007	-73662.7	-26826.3	59665.35	-19147.8	102954.5	-17698.1	3106.169	0.005992	160.8718	160.9799

Quarterly Fit

year	**quarter**	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090binf***	***a090b119***	***a120binf***	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090binf***	***a090b119***	***a120binf***	V_0	q	**BIC**	**AIC**
2015	1	113260	83630	64160	25115	39830			-8292.55	9533.789	4023.454	-2714.92	-32773.2			9571.056	0.038737	99.93285	100.714
2015	2	126345	102280	68450	22310	39165			-3888.9	2648.422	5478.816	613.8997	-32337.3			11278.93	0.040395	99.25652	100.0376
2015	3	121925	87780	58290	21275	31790			-4547.23	5904.222	2898.779	-4378.83	-27291.3			11033.37	0.043751	97.84386	98.62499
2015	4	96690	75190	57310	21110	31200			-5894.89	6380.388	3182.124	-834.962	-24686.9			8249.993	0.038166	96.97401	97.75514
2016	1	98600	71795	48650	16660	29350			-4019.64	5025.856	2464.795	-2137.52	-25375.4			8846.004	0.042923	96.97579	97.75691
2016	2	113035	87695	59525	21595	37780			-4963.69	4557.099	5207.933	-1646.92	-31874.3			9964.83	0.040574	99.22445	100.0056
2016	3	111330	89330	64380	23200	35870			-5365.77	4882.619	4701.661	-439.608	-28679.6			9657.112	0.038655	98.24703	99.02815
2016	4	99275	80880	64735	24525	37425			-7516.85	6726.756	4713.623	1217.797	-28297.7			8193.158	0.035312	98.40477	99.18589
2017	1	100235	82725	62370	24125	44190			-7776.89	5430.431	7409.06	1682.062	-35060.2			8258.873	0.035376	100.3872	101.1684
2017	2	123895	99145	76490	25875	51040			-8671.66	7835.684	5750.711	3229.629	-41180.2			10371.2	0.036621	101.9335	102.7146
2017	3	115040	94575	81310	29830	50170			-11147	9455.843	5636.946	5063.817	-36783.1			9150.643	0.033087	101.2127	101.9939
2017	4	105970	96565	81620	33075	50235			-9947.34	4889.604	8450.629	6489.724	-33606.8			8327.909	0.030586	100.3467	101.1279
2018	1	105460	85690	77730	31165	61075			-16704.5	10438.41	10046.05	9044.264	-43431.8			7642.999	0.029436	103.2828	104.0639
2018	2	131070	106870	93545	37965	61300			-15523.7	12009.47	8877.06	5052.883	-44024.7			10098.05	0.031823	103.2228	104.0039
2018	3	118755	106225	92915	41265	64560			-15866.2	7163.593	12694.53	8564.347	-42014.6			8815.904	0.02863	102.9586	103.7397
2018	4	109860	101830	98895	40675	68900			-17100.5	6879.587	9793.115	16308.89	-40055.4			7808.583	0.025786	102.9658	103.7469
2019	1	107765	92120	84130	34600	69105			-18979.5	8560.117	12766.85	13404.15	-46241.1			7545.243	0.027308	104.1363	104.9175
2019	2	133425	112230	96610	37345	72430			-16880.2	10373.32	11702.17	9884.255	-52728.7			10120.42	0.030788	104.9179	105.699
2019	3	121170	105905	90105	35695	71220			-16258.3	7479.849	13177.28	11446.66	-50612.1			9039.796	0.029535	104.5827	105.3638
2019	4	107615	92770	82760	36390	64505			-17547.3	8068.006	12873.92	9964.259	-42931.4			7682.383	0.027899	103.3316	104.1127
2020	1	141330	96630	85765	42750	146285	23220	123070	-100275	-29069.6	16169.8	55650.91	-26510.8	61628.12	-35281.9	3133.976	0.010303	156.3049	156.4131
2020	4	142440	109620	107585	51560	149010	26115	122895	-84916.5	-19791.3	19315.75	59530.63	-37326.3	61076.92	-46711.1	4457.975	0.01267	155.8796	155.9878
2021	1	148945	109325	95515	50095	149600	22655	126945	-96369.5	-25909.7	24687.49	58279	-34604.8	64843.99	-46773	4055.903	0.011952	156.8273	156.9355
2021	2	200195	152400	139565	64030	175715	31525	144185	-100039	-8636.38	43454.7	73267.61	-67789.2	61486.98	-78655.7	7952.826	0.016494	159.5719	159.6801
2021	3	160135	178810	184600	97440	291595	51310	240290	-98809.6	-73423	-16590.2	78594.87	-31317.2	113017	-37904.5	4623.134	0.008351	160.5712	160.6794
2021	4	135850	151660	178815	105960	343260	58010	285250	-91529.1	-71307.9	-41593.9	53339.95	-19943	106341	-14916.5	3290.004	0.005948	159.1338	159.242
2022	1	173840	149430	156055	90075	320985	51250	269740	-132007	-73662.7	-26826.3	59665.35	-19147.8	102954.5	-17698.1	3106.169	0.005992	160.8718	160.9799

Appendix II

Appendix II Table: Observation, Model, and Residuals

All Fit

		Observation					Residuals					Model			
year	**quarter**	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090b119***	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090b119***	V_0	q	**BIC**	**AIC**
2015	1	113260	83630	64160	25115		4850.662	29637.74	26071.4	8578.718		10532.78	0.035105	2359.339	2353.849
2015	2	126345	102280	68450	22310		-8234.34	10987.74	21781.4	11383.72					
2015	3	121925	87780	58290	21275		-3814.34	25487.74	31941.4	12418.72					
2015	4	96690	75190	57310	21110		21420.66	38077.74	32921.4	12583.72					
2016	1	98600	71795	48650	16660		19510.66	41472.74	41581.4	17033.72					
2016	2	113035	87695	59525	21595		5075.662	25572.74	30706.4	12098.72					
2016	3	111330	89330	64380	23200		6780.662	23937.74	25851.4	10493.72					
2016	4	99275	80880	64735	24525		18835.66	32387.74	25496.4	9168.718					
2017	1	100235	82725	62370	24125		17875.66	30542.74	27861.4	9568.718					
2017	2	123895	99145	76490	25875		-5784.34	14122.74	13741.4	7818.718					
2017	3	115040	94575	81310	29830		3070.662	18692.74	8921.402	3863.718					
2017	4	105970	96565	81620	33075		12140.66	16702.74	8611.402	618.7181					
2018	1	105460	85690	77730	31165		12650.66	27577.74	12501.4	2528.718					
2018	2	131070	106870	93545	37965		-12959.3	6397.74	-3313.6	-4271.28					
2018	3	118755	106225	92915	41265		-644.338	7042.74	-2683.6	-7571.28					
2018	4	109860	101830	98895	40675		8250.662	11437.74	-8663.6	-6981.28					
2019	1	107765	92120	84130	34600		10345.66	21147.74	6101.402	-906.282					
2019	2	133425	112230	96610	37345		-15314.3	1037.74	-6378.6	-3651.28					
2019	3	121170	105905	90105	35695		-3059.34	7362.74	126.4021	-2001.28					
2019	4	107615	92770	82760	36390		10495.66	20497.74	7471.402	-2696.28					
2020	1	141330	96630	85765	42750	23220	-23219.3	16637.74	4466.402	-9056.28	10473.72				
2020	4	142440	109620	107585	51560	26115	-24329.3	3647.74	-17353.6	-17866.3	7578.718				
2021	1	148945	109325	95515	50095	22655	-30834.3	3942.74	-5283.6	-16401.3	11038.72				
2021	2	200195	152400	139565	64030	31525	-82084.3	-39132.3	-49333.6	-30336.3	2168.718				
2021	3	160135	178810	184600	97440	51310	-42024.3	-65542.3	-94368.6	-63746.3	-17616.3				
2021	4	135850	151660	178815	105960	58010	-17739.3	-38392.3	-88583.6	-72266.3	-24316.3				
2022	1	173840	149430	156055	90075	51250	-55729.3	-36162.3	-65823.6	-56381.3	-17556.3				

Yearly Fit

year	**quarter**	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090b119***	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090b119***	V_0	q	**BIC**	**AIC**
2015	1	113260	83630	64160	25115		-1158.73	7986.127	-2798.75	-7504.79		10466.18	0.04263	295.5162	293.971
2015	2	126345	102280	68450	22310		-14243.7	-10663.9	-7088.75	-4699.79					
2015	3	121925	87780	58290	21275		-9823.73	3836.127	3071.251	-3664.79					
2015	4	96690	75190	57310	21110		15411.27	16426.13	4051.251	-3499.79					
2016	1	98600	71795	48650	16660		4822.839	14336.63	10209.66	760.1701		9603.923	0.041739	287.3378	285.7926
2016	2	113035	87695	59525	21595		-9612.16	-1563.37	-665.342	-4174.83					
2016	3	111330	89330	64380	23200		-7907.16	-3198.37	-5520.34	-5779.83					
2016	4	99275	80880	64735	24525		4147.839	5251.632	-5875.34	-7104.83					
2017	1	100235	82725	62370	24125		8045.769	15714.21	11580.73	1150.221		9805.408	0.037609	292.1403	290.5951
2017	2	123895	99145	76490	25875		-15614.2	-705.793	-2539.27	-599.779					

2017	3	115040	94575	81310	29830		-6759.23	3864.207	-7359.27	-4554.78					
2017	4	105970	96565	81620	33075		2310.769	1874.207	-7669.27	-7799.78					
2018	1	105460	85690	77730	31165		5592.928	22903.46	10664.07	2930.694		9848.165	0.034194	298.8199	297.2747
2018	2	131070	106870	93545	37965		-20017.1	1723.46	-5150.93	-3869.31					
2018	3	118755	106225	92915	41265		-7702.07	2368.46	-4520.93	-7169.31					
2018	4	109860	101830	98895	40675		1192.928	6763.46	-10500.9	-6579.31					
2019	1	107765	92120	84130	34600		5080.121	16198.16	2246.659	-2296.08		10060.55	0.035062	296.5409	294.9957
2019	2	133425	112230	96610	37345		-20579.9	-3911.84	-10233.3	-5041.08					
2019	3	121170	105905	90105	35695		-8324.88	2413.165	-3728.34	-3391.08					
2019	4	107615	92770	82760	36390		5230.121	15548.16	3616.659	-4086.08					
2020	1	141330	96630	85765	42750	23220	-9456.7	23947.41	5386.049	-11299.3	8230.672	11922.19	0.03734	194.8112	194.2061
2020	4	142440	109620	107585	51560	26115	-10566.7	10957.41	-16434	-20109.3	5335.672				
2021	1	148945	109325	95515	50095	22655	5479.565	51967.73	45828.64	10796.97	38236.97	13437.42	0.031121	417.1811	415.1896
2021	2	200195	152400	139565	64030	31525	-45770.4	8892.729	1778.638	-3138.03	29366.97				
2021	3	160135	178810	184600	97440	51310	-5710.44	-17517.3	-43256.4	-36548	9581.971				
2021	4	135850	151660	178815	105960	58010	18574.56	9632.729	-37471.4	-45068	2881.971				
2022	1	173840	149430	156055	90075	51250	-13889	20251.57	-4724.24	-23146.6	15678.41	13856.26	0.030399	100.4951	101.2762

Quarterly Fit

year	quarter	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090b119***	***a000b014***	***a015b029***	***a030b059***	***a060b089***	***a090b119***	V_0	q	BIC	AIC
2015	1	113260	83630	64160	25115		-4103.86	7467.277	-1767.16	-6585.72		10130.23	0.04164	71.60919	72.8366
2015	2	126345	102280	68450	22310		-604.204	722.9719	709.1957	-2386.22		11731.77	0.04252	60.32125	61.54866
2015	3	121925	87780	58290	21275		-2307.75	4281.675	-424.174	-6213.74		11361.57	0.045477	69.02685	70.25426
2015	4	96690	75190	57310	21110		-2717.68	4884.678	-1229	-3878.26		8669.228	0.040657	67.95732	69.18473
2016	1	98600	71795	48650	16660		-1808.75	3498.158	-789.895	-3985.26		9165.455	0.044971	66.35426	67.58167
2016	2	113035	87695	59525	21595		-1644.12	2605.865	436.2687	-4612.47		10424.02	0.043014	66.22009	67.44751
2016	3	111330	89330	64380	23200		-1905.18	3156.881	-169.049	-3731.13		10118.32	0.041041	65.75282	66.98023
2016	4	99275	80880	64735	24525		-2995.85	5156.43	-1300.44	-3450.07		8761.712	0.038417	68.06961	69.29703
2017	1	100235	82725	62370	24125		-2209.03	3428.41	15.85632	-3957.7		8963.316	0.039199	66.38941	67.61682
2017	2	123895	99145	76490	25875		-2808.68	5402.516	-2223.11	-2557.01		11128.45	0.040036	68.02035	69.24776
2017	3	115040	94575	81310	29830		-4192.39	7687.695	-3244.53	-2493.43		9995.656	0.03692	70.63792	71.86533
2017	4	105970	96565	81620	33075		-2473.4	3798.388	-677.937	-2285.07		9200.098	0.034584	65.55655	66.78396
2018	1	105460	85690	77730	31165		-5395.38	9200.44	-3069.1	-3800.79		8952.3	0.03563	72.18754	73.41495
2018	2	131070	106870	93545	37965		-6082.25	10144.55	-2766.83	-5393.92		11223.3	0.036231	73.18626	74.41367
2018	3	118755	106225	92915	41265		-4600.22	6451.959	-237.12	-4953.66		10096.04	0.033757	70.37074	71.59815
2018	4	109860	101830	98895	40675		-4252.83	7585.669	-3882.35	-296.927		9210.912	0.031498	70.52364	71.75105
2019	1	107765	92120	84130	34600		-5001.75	8224.752	-2579	-3218.27		9116.756	0.034261	71.27945	72.50686
2019	2	133425	112230	96610	37345		-4860.57	8382.228	-2827.9	-3580.58		11537.62	0.036134	71.45889	72.6863
2019	3	121170	105905	90105	35695		-3668.71	6013.14	-1617.06	-3024.48		10498.97	0.035424	68.95776	70.18518
2019	4	107615	92770	82760	36390		-5068.41	7557.204	-1047.83	-4844.56		9092.477	0.03417	71.1945	72.42191
2020	1	141330	96630	85765	42750	23220	-10125.1	17590.4	-3902.89	-16697.7	2832.311	12029.97	0.039648	97.1037	97.88482
2020	4	142440	109620	107585	51560	26115	-9353.43	16996.28	-7603.7	-14716.9	10728.08	11895.49	0.035478	97.45421	98.23533
2021	1	148945	109325	95515	50095	22655	-9246.67	15602.91	-3332.45	-19432.1	8007.883	12710.33	0.038383	97.55717	98.3383
2021	2	200195	152400	139565	64030	31525	-10819	20382.14	-9256.42	-19228.1	13276.91	17131.38	0.037441	99.54801	100.3291
2021	3	160135	178810	184600	97440	51310	3813.416	3116.883	-13814.4	-15908	30222.03	14019.94	0.028311	100.404	101.1851
2021	4	135850	151660	178815	105960	58010	-154.007	9447.507	-15287.8	-18279.3	29670.68	11380.41	0.025187	100.9387	101.7199
2022	1	173840	149430	156055	90075	51250	-13889	20251.57	-4724.24	-23146.6	15678.41	13856.26	0.030399	100.4951	101.2762